JEROEN VAN OOSTRUM

## Applying mathematical models to surgical patient planning

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## Toepassen van mathematische modellen voor de planning van chirurgische patiënten

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## Contents

Acknowledgements ..... $i$
Chapter 1 - Introduction ..... 1

1. General introduction and research motivation ..... 3
1.1. Organizational aspects ..... 3
1.2. Operations Research aspects ..... 4
2. Background and literature overview ..... 5
2.1. Background ..... 5
2.2. A hierarchical overview of OR planning and ..... 6
3. Success factors for planning approaches ..... 8
4. Comparing surgical scheduling approaches ..... 9
4.1. Decentralized and centralized planning approaches: ..... 9
4.2. Potential advantages of the MSS approach ..... 11
5. A 7-stepwise approach for master surgical scheduling ..... 12
5.1. Scope of the MSS ..... 12
5.2. Data gathering ..... 12
5.3. Capacity planning ..... 12
5.4. Define a set of recurrent standard case types ..... 13
5.5. Construction of the Master Surgical Schedule ..... 14
5.6. Execute the Master Surgical Schedule ..... 14
5.7. Update a Master Surgical Schedule ..... 15
6. Thesis outline 15

Chapter 2 - Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical21 case scheduling

1. Introduction ..... 23
2. Methods ..... 24
2.1. Data ..... 24
2.2. Mathematical representation of Erasmus MC's surgical case scheduling ..... 25
2.3. Planned slack and the portfolio effect ..... 27
2.4. Organizational barriers ..... 28
2.5. Advanced mathematical algorithms ..... 29
2.6. Experimental design ..... 29
3. Results ..... 31
4. Discussion ..... 33
Chapter 3 - A method for clustering surgical cases to ..... 37 allow master surgical scheduling
5. Introduction ..... 39
6. Background ..... 40
7. Literature ..... 41
8. Problem definition ..... 42
9. Solution approach ..... 42
5.1. Modeling volume of dummy surgeries ..... 43
5.2. Modeling resource demand variability ..... 43
5.3. Solution heuristic ..... 44
10. Case study ..... 44
6.1. Data ..... 45
6.2. Case study results ..... 46
6.3. Discussion ..... 47
11. Conclusion ..... 48
Chapter 4 - A master surgical scheduling approach for ..... 51 cyclic scheduling in operating room departments
12. Introduction ..... 53
13. Related literature ..... 54
14. Problem description ..... 55
3.1. Formal problem description ..... 57
3.2. Base model ..... 57
15. Solution approach ..... 59
4.1. Phase 1 ..... 60
4.2. Phase 2 ..... 64
16. Computational experiments ..... 66
5.1. Instance generation ..... 66
5.2. Test results ..... 67
17. Conclusions and further research ..... 70
Chapter 5 - Fewer intensive care unit refusals and a higher capacity utilization by using a cyclic surgical case ..... 75
schedule
18. Introduction ..... 77
19. Materials and methods ..... 78
20. Results ..... 81
21. Discussion ..... 82
Chapter 6 - Implementing a master surgical scheduling ..... 87 approach in an acute general hospital
22. Introduction ..... 89
23. Dealing with implementation problems: an organizational ..... 90 approach
2.1. Specialty based focused units ..... 90
2.2. Delivery based focused units ..... 91
2.3. Procedure based focused units ..... 91
2.4. General purpose units ..... 92
2.5. Implications for practice ..... 92
24. Case background ..... 93
25. Solving the surgical scheduling problem at Beatrix Hospital ..... 94
4.1. Step 1: Scope of the MSS ..... 96
4.2. Step 2: Data gathering ..... 96
4.3. Step 3: Capacity planning ..... 97
4.4. Step 4: Define a set of recurrent standard case types ..... 98
4.5. Step 5: Construction of the Master Surgical Schedule ..... 99
4.6. Step 6: Execute the Master Surgical Schedule ..... 99
4.7. Step 7: Update a Master Surgical Schedule ..... 99
26. Results ..... 100
27. Discussion ..... 100
28. Conclusion ..... 101
Chapter 7 - Requirements for a full service level ..... 105agreement at an operating room department - a case study
29. Introduction ..... 107
30. Methods ..... 109
2.1. Modeling ..... 110
2.2. Modeling elective surgical schedules ..... 111
2.3. Modeling emergency surgical cases ..... 112
2.4. Modeling the OR day coordination ..... 113
2.5. Scenario modeling ..... 114
31. Results ..... 115
32. Discussion and Conclusion ..... 118
Chapter 8 - Closing emergency operating rooms improves ..... 123
efficiency
33. Introduction ..... 125
34. Data and methods ..... 126
35. Results ..... 128
36. Discussion ..... 128
Appendix to Chapter 8 ..... 131
Chapter 9 - A simulation model for determining the optimal size of emergency teams on call in the operating ..... 133 room at night
37. Introduction ..... 135
38. Methods ..... 136
2.1. Modeling ..... 137
2.2. Precalculations ..... 140
2.3. Scenarios ..... 140
39. Results ..... 142
40. Discussion ..... 145
Chapter 10 - Concluding remarks and implications ..... 149
Nederlandse samenvatting (Summary in Dutch) ..... 155
Curriculum Vitae ..... 159

## Chapter 1

## Introduction

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## Chapter 1

## Introduction

## 1. General introduction and research motivation

European countries face an ageing population and rising health care costs (OECD, 2008). At the same time, the general public demands the latest technologies, combined with short waiting and access times. This growing demand for cure and care provided by hospitals puts a strong focus on effectiveness and efficiency. Hospital management is challenged to deal with the seemingly conflicting objectives of low costs, high quality of care, and high quality of labor. Health care logistics can potentially make a major contribution to maintaining high level care and affordable costs.

One of the major challenges of health care logistics in hospitals is to improve processes related to surgical case scheduling. Surgical scheduling is a complex task in hospitals, and a popular topic among academic researchers. Typically, the focus is on maximizing operating room utilization and revenues. However, an operating room department is not a stand-alone unit within a hospital. Studies on academic models and real implementations of strategies that optimize surgical scheduling taking into account the other partners in the care chain.

This thesis describes the concept of master surgical scheduling in a 7 -stepwise approach. This approach cyclically executes a master schedule of surgical case types. A master surgical schedule not only allows for optimization of operating room utilization, it creates robustness and minimizes overtime while it also makes resource demands on other departments, such as wards, more predictable. Master surgical scheduling is a generic framework that helps hospitals to improve their logistics. This thesis provides the reader with organizational prerequisites, mathematical models, managerial aspects, and practical insights into the suggested master surgical scheduling approach.

Dealing with emergency arrivals in operating room departments is for surgeons and staff one of the most demanding tasks. Within a master surgical scheduling approach the thesis provides insights into how to deal with emergency surgical patients arriving during day and night times. The proposed models may be integrated in the master surgical scheduling approach, but can function in conjunction with other elective scheduling approaches as well. Together with the master surgical scheduling approach this thesis provides a logistical approach to improve both the operational and tactical level of operating room management.

### 1.1. Organizational aspects

Hospital organizations are organizations with a complex structure. An operating room department is one of those places where many workers cooperate to deliver complex and
high-level care to patients. About sixty percent of the inpatient hospital admissions are surgery related. Hence, often one of the biggest concerns of hospital management is the manageability of surgical scheduling processes. Any logistical problem in surgical scheduling has a substantial impact on a hospital organization. Moreover, such disruptions due to logistical problems cause both frustrations of staff and inefficiency. Many actors are involved in the process of surgical case scheduling. This can easily lead to inefficiencies in information transfer and unnecessarily repeated work. Hospital management wants to keep the surgical scheduling processes efficient, and at the work floor level easy and transparent.

Sometimes patients are scheduled months ahead, sometimes they are scheduled just minutes in advance. Hence, flexibility in hospital organizations is a prerequisite for providing optimal care to patients. The argument that flexibility is required to schedule emergency patients is particularly used by physicians. However, the argument is often misused to claim more resources than are necessary. For example, requests by surgical departments for operating room capacity often substantially exceed the amount of operating room time that is actually needed. This leads to underutilization of expensive and scarce operating room capacity. Finding a good balance between efficiency and flexibility to deal with emergencies is hence of paramount importance.

Physicians are high-level educated professionals who work with individual patients and who perform multiple tasks, ranging from seeing patients at outpatient clinics and performing surgery to research and managerial tasks. From an organizational perspective, physicians have a substantial amount of formal and informal power. Any change in a logistical process should therefore be accounted by this group of actors. Therefore, to be applicable, any logistical model should take account of the autonomy and particularities of this group of actors. Therefore any logistical improvement project needs to discuss these limits carefully. Operations research models can help by providing analytical insights for such discussions.

Personnel at wards and operating room departments are employed by hospitals. Strict labor rules apply for this group of actors in hospitals such that work schedules of nurses are highly regulated. For example, changing staffing levels of regularly employed staff can only be done weeks in advance. It is therefore important that forecasts on the required demand are close to the actual demand, because deviations generally increase costs. Hence, stability of patient flows improves efficient usage of this scarce resource.

### 1.2. Operations Research aspects

Operations Research can generate models to improve patient planning. However, improving hospital logistics by such models is only possible when they actually get implemented. A prerequisite for such models is a good trade-off between a correct representation of reality and understandability. Models that include huge numbers of
different types of input and output parameters and variables are hard to understand by practitioners. On the other hand, models that are built up by too few parameters and variables may lack sufficient detail. Hence, logistical models for operating room planning and scheduling require thorough modeling such that they are both understandable and a sufficiently correct representation of reality.

Another requirement for models to be usable in practice is their adherence to organizational conditions as explained in the previous subsection. When performing a project, often not all these conditions are clear at a project start. Practitioners frequently do not want to choose between objectives of efficiency, quality of labor, and quality of care. Mathematical models therefore generally have multi-criteria objectives, while it might be impossible to determine weight factors from practice. Additionally, hospital staff often adds restrictions during logistical projects. These restrictions might lack validity from a logistical prospective and may be due to personal preferences. They might even prevent finding a feasible solution at all. Operations researchers working with logistical models in hospital practice should hence explicitly focus on clearness and check carefully the validity and impact of organizational constraints to provide practice with useful and applicable models.

Scheduling decisions in the context of, for example, operating room departments face fast increasing numbers of possible solutions. In itself this leads to computational complexity. Moreover, problem solving in hospitals is often complicated due to the inherent stochastic nature of health care processes. Logistical solutions should therefore be robust against such stochastic uncertainty. Besides this, the ongoing development of information technology makes that more data and other sources of information come available. The combination of increasing availability of data, huge sets of possible solutions and the stochastic nature of hospital processes makes hospital logistics an interesting application area for operations research from both a technical and a practical perspective.

## 2. Background and literature overview

### 2.1. Background

Within the relatively small part of the operations research/management science research community that is active in the field of healthcare management (Carter, 2002), optimization of operating room (OR) department planning and scheduling has always been a popular subject (Dexter, et al., 2004; Gerchak, et al., 1996; Guinet and Chaabane, 2003; Hans, et al., 2008; Lamiri, et al., 2008). As approximately $60 \%$ of all inpatient admissions consist a visit to an OR department, and various scarce and expensive resources are involved, it is apparent that its efficiency is paramount.

The OR department is often regarded as a production facility with many process uncertainties, like emergencies (Wullink, et al., 2007), surgery durations (Strum, et al., 2000) and resource availability (McIntosh, et al., 2006). It is myopic to focus on just the OR department itself. Its schedule influences processes throughout the hospital (van Oostrum, et al., 2008). Also, other departments like the intensive care units (ICUs) and wards pose constraints on the OR schedule that may not be ignored (e.g., bed availability after surgery) (Vanberkel and Blake, 2007). From an operations research perspective, OR planning and scheduling obviously poses very challenging problems. From the OR manager's perspective, the challenge is to actually implement the resulting tools (Stoop and Wiers, 1996). The influence of various stakeholders, with varying degrees of autonomy, is often substantial. In the case of OR scheduling, surgical services (with surgeons), surgery and anesthesia assistants, and anesthesiologists, all have a considerable influence on OR management (Glouberman and Mintzberg, 2001a; b; Mintzberg, 1997). Intelligent OR planning and scheduling approaches proposed in the literature often fail to account for this, which explains their relatively marginal impact in practice (Harper, 2002; Roth and van Dierdonck, 1995) and the small number of successful implementations in the literature (Blake and Donald, 2002).

As we shall argue, Master Surgical Scheduling (MSS) is a very promising approach from both perspectives. It cyclically executes a master schedule of surgery types, which contains slots for surgery types that recur at least once every cycle (of, say, 4 weeks). In most hospitals and especially clinics, a large part of the case mix in the OR department is recurrent. Such recurrent surgery types can be scheduled in advance in an MSS. From an operations research perspective an MSS can be optimized regarding OR utilization, robustness, overtime, resource conflicts (e.g. limited X-rays), etc. Moreover, it can be drawn up to optimize the inflow into subsequent departments (e.g., ICU, wards). From an OR manager's perspective, the cyclic approach lowers the management burden of making a new schedule every week. It also allows early coordination of personnel and departments involved. More importantly, the medical autonomy is maintained: surgeons remain in charge of selecting patients for particular slots in the schedule. Different MSS approaches have been proposed in the literature (Belien and Demeulemeester, 2007; Blake and Donald, 2002; Van Houdenhoven, et al., 2007c; van Oostrum, et al., 2008; Vissers, et al., 2005). Nevertheless, various MSS implementation issues have not been dealt with.

### 2.2. A hierarchical overview of OR planning and scheduling

This section gives an overview of the various OR planning and scheduling problems, and the solution approaches suggested in the literature. We focus entirely on resource capacity planning and scheduling problems, and discard other managerial areas such as medical planning, material coordination, and financial management. To position the various OR planning and scheduling problems we use the classical hierarchical decomposition of the
managerial functions into four levels: strategic, tactical, offline and online operational control (Vissers, et al., 2001). The remainder of this section subsequently addresses each level. For a complete overview of the literature concerning OR planning and scheduling we refer to (Denton, et al., 2007; Dexter, et al., 2004; Dexter, et al., 1999a; b; Guinet and Chaabane, 2003; Hans, et al., 2008; McIntosh, et al., 2006; Pham and Klinkert, 2008; Sier, et al., 1997; Van Houdenhoven, et al., 2007b; Zhou and Dexter, 1998).

## Strategic OR planning and scheduling

To reach organizational goals, the strategic level addresses the dimensioning of core OR resources, such as (inpatient, outpatient, emergency) ORs, personnel, instruments (e.g. X-rays), etc. It also involves case mix planning, i.e. the selection of surgery types, and the determination of the desired patient type volumes (Vissers, et al., 2002). Agreements are made with surgical services / specialties concerning their annual patient volumes and assigned OR time. The dimensioning of subsequent departments' resources (e.g. ICUs, ward beds) is also done (Vanberkel and Blake, 2007). Strategic planning is typically based on historical data and/or forecasts. The planning horizon is typically a year or more.

## Tactical OR planning and scheduling

The tactical level addresses the usage of the resource on a medium term, typically with a planning horizon of several weeks (Blake and Donald, 2002; Wachtel and Dexter, 2008). The actual patient demand (e.g. waiting lists, appointment requests for surgery) is used as input. In this stage, the weekly OR time is divided over specialties or surgeons, and elective patients are assigned to days. For the division of OR time, two approaches exist. When a closed block planning approach is used, each specialty will receive a number of OR blocks (usually OR-days). In an (uncommon) open block planning approach, OR time is assigned following the arrival of requests for OR time by surgeons.

On the tactical level, the surgery sequence is usually not of concern. Instead on this level is verified whether the planned elective surgeries cause resource conflicts for the OR, for subsequent departments (ICU, wards), or for required instruments with limited availability (e.g. X-rays). The design of a Master Surgical Schedule is a tactical planning problem.

## Offline operational OR planning and scheduling

The offline operational level addresses the in advance scheduling of resources and sequencing of activities, typically with a planning horizon of a week (Sier, et al., 1997). It encompasses the rostering of OR-personnel, and the add-on scheduling of semi-urgent surgeries in reserved or unused OR-time (Dexter, et al., 1999b). In addition, it addresses the sequencing of surgeries (Denton, et al., 2007), to prevent critical resource conflicts, e.g. regarding X-rays, instrument sets, surgeons, etc. When there are no emergency ORs, the sequencing of the elective surgeries can also aid in spreading the planned starting times of
elective surgeries (which are "break-in moments" for emergency surgeries) in order to reduce the emergency surgery waiting time (Wullink, et al., 2007).

## Online operational OR planning and scheduling

The online operational level addresses the monitoring and control of the OR activities during the day. Obviously at this level of control, all uncertainty materializes and has to be dealt with. If necessary, surgeries are rescheduled, or even cancelled (Dexter, et al., 2004; McIntosh, et al., 2006). This is usually done by a day coordinator in the OR department. Emergency surgeries, which have to be dealt with as soon as possible, are scheduled, and emergency OR teams may have to be assembled and dispatched to the first available OR. If there are emergency ORs, these emergency surgeries are dispatched in these ORs. If there are no such ORs, they are scheduled somewhere in the elective surgical schedule.

## 3. Success factors for planning approaches

We subsequently discuss several criteria that influence the success of a planning approach: data requirements, resource utilization, robustness, alignment with planning of relevant other departments or resources, autonomy of surgeons, managerial workload, and financial control.

## Data requirements

Intelligent planning approaches are data intensive. A larger amount of data or higher level of detail available generally gives more insight in processes and leads to better predictions (Dexter, et al., 2007). On the one hand, the quality of planning potentially increases. On the other hand, a smaller amount of data or a lower level of detail required makes it more likely that these data can be obtained.

## Resource utilization

The OR department is one of the most expensive resources in a hospital. Therefore, planning approaches generally try to maximize the utilization of this department. As we shall argue with the following assessment criterion, utilization by itself is not a good performance indicator - it should always be jointly considered with robustness.

## Robustness

Robustness of a planning approach can have two interpretations: robustness against disruptions and robustness against 'cheating'. The former is the extent in which an approach is able to deal with disruptions like emergency arrivals, resource unavailability, overtime, and late cancellations. Moreover, a robust approach should deal with such disruptions on a short term. A high responsiveness to disruption reduces the potential number of affected processes in a hospital.

The latter is the extent in which an approach is able to cope with actors trying to 'trick' the planning in their favor. As an example, a surgeon may request more OR time than he actually needs. A planning approach that can handle both disruptions and prevent actors to cheat the system leads to stable schedules and is thus optimally robust.

Robustness against disruptions is typically obtained by using slack time or slack capacity. For example, in an elective surgery, usually some time is reserved at the end of the regular program to deal with possible disruptions. Obviously, the more robust the program, the more time needs to be reserved, and thus the lower the OR utilization. Consequently, robustness and utilization should always be jointly considered as performance criteria (Van Houdenhoven, et al., 2007a).

## Alignment with planning of relevant other departments or resources

An OR planning approach should be aligned with the planning of other relevant departments or resources, such as wards, outpatient clinics, and central sterilization departments. A mismatch between, for instance, the surgical schedules and the scheduling of wards, can seriously affect resource utilization and lead to surgery cancellations.

## Autonomy of surgeons

Healthcare delivery necessitates medical decision making by professionals. This includes decisions on when to deliver care, which are not always based on medical necessity. When this is a medical necessity, a planning approach should incorporate sufficient flexibility to allow for this. Here, the surgeon's autonomy is essential.

## Managerial workload

Many logistical concepts like just-in-time and workload control are focused on reducing system complexity, and thereby the managerial workload. This workload consists of the required effort to make planning decisions and maintain operational control. The required managerial workload is influenced by a planning and scheduling approach.

## Financial control

The more centralized a planning approach, the more it allows financial monitoring and control of the OR department's production. This is particularly important for countries with healthcare systems that apply elements of market competition, such as yard stick competition.

## 4. Comparing surgical scheduling approaches

### 4.1. Decentralized and centralized planning approaches: advantages and disadvantages

We discern between centralized and decentralized planning approaches. In a decentralized approach, surgeons decide on the assignment of patients. In a centralized approach, a
central planner decides on the eventual division of OR time and assignment of patients. Both approaches require hospital information systems to store data and monitor production. The allocation of decision making power should be reflected in and supported by such decision support systems and information systems. In a way these systems offer an implementation of the chosen allocation of decision making power. We compare advantages and disadvantages of the centralized and decentralized planning approaches, using the success factors outlined in Section 3. The comparison is summarized in Table 1.

A decentralized planning approach offers surgeons full autonomy. It requires very limited data, and reduces the managerial workload at a tactical level. However, the lack of coordination amongst surgeons, and between surgeons and other departments, deteriorates predictability of patient flows, robustness, and resource utilization and necessitates a more intensive online operational control. A decentralized approach is not robust against surgeons trying to 'cheat' the system in their advantage, e.g. by claiming more OR time than actually required, thus leading to lower resource utilization. Finally, although a decentralized planning approach allows for monitoring, it complicates the financial control of the OR department's production.

A centralized planning approach offers little autonomy to surgeons. It requires substantial amounts of data and comes with a substantial workload at a tactical level. The resulting schedules are characterized by high robustness and high utilization. The OR

| Decentralized planning approach | Centralized planning approach |
| :--- | :--- |
| Full surgeon autonomy | Little surgeon autonomy |
| Requires limited data | Requires substantial amount of data |
| Reduces managerial workload at tactical | Substantial workload at tactical level |
| level |  |
| Requires intensive online operational | Requires online operational control |
| control | Good integration of multiple planning |
| Results in lack of coordination | processes |
| Low robustness against cheating, low | High robustness against cheating, high <br> predictability of patient flows, and low |
| predictability of patient flows, and high |  |
| utilization | utilization |

Table 1: Summary of the advantages and disadvantages of decentralized and centralized planning approaches
department has to gather and record data of the particularities of all surgeons, patients, and treatments types, and continuously update these data to provide the required process insight to the planner. Since fewer actors are involved in a centralized planning approach, integration with other planning processes within the hospital is easier. Nevertheless, this alignment still requires substantial effort. A major disadvantage of this planning approach is the low autonomy of the surgeons. Surgeons are not allowed to decide when to operate a patient, which might result in surgeons 'cheating' the approach by labeling all patients as urgent. Finally, a centralized planning approach allows for monitoring and financial control.

### 4.2. Potential advantages of the MSS approach

An MSS approach comprises of a schedule of recurrent surgery types, which is cyclically executed. The goal of an MSS approach is to optimize utilization, level the workload, and construct a robust schedule. Patients are assigned to the appropriate slots in this schedule. The planning horizon of the schedule is called the MSS cycle length.

The MSS approach combines advantages of both centralized and decentralized approaches. The main advantages are that it offers the autonomy of medical decision making to surgeons (who may assign patients to slots), while at the same time it yields a high utilization, robustness of schedules, a low degree of required organizational effort at operational level, and offers financial control. Although an MSS approach requires a substantial amount of data, it reduces the managerial workload as compared to a nonrepetitive centralized planning approach.

The repetitive execution of an MSS approach structures the generally chaotic working practice in OR departments. Hospital departments, such as wards, central sterilization departments, and X-rays, can easily anticipate future demands, thereby reducing the required slack at these departments and improving their efficiency. An MSS thus supports alignment of these resources with the OR department.

An MSS offers all the advantages of a centralized planning approach, regarding optimization of resource utilization and workload leveling. Clustering surgery types with a high variability in a single operating room, for example, might be beneficial for reducing overtime (Hans, et al., 2008), and enables management to predict surgery start times more accurately. Furthermore, surgery types that require movable resources such as X-rays can be clustered together in one OR to reduce waiting time for such equipment. Consequently, MSS reduces the managerial burden of operational control.

## 5. A 7-stepwise approach for master surgical scheduling in practice

We present a 7- stepwise approach for implementing an MSS in practice (see also Figure 1). In this thesis we address models that are required for the seven steps and address potential issues that might be encountered.

### 5.1. Scope of the MSS

The first step is to define the scope, i.e., the resources and organizational units to be included in the MSS. These are typically the expensive and scarce resources for which increased utilization is beneficial. As an example, an MSS could also cover ICUs, wards, and medical departments. Including a resource or unit is only beneficial if it results in an improved patient flow.

### 5.2. Data gathering

Planning and scheduling relies heavily on reliable data (Harper, 2002). Developing an MSS requires at least a year of historical data concerning all processes and resources within its scope. Hospitals routinely collect substantial amounts of process data (Harper, 2002). However, these data are often incomplete and polluted, which complicates logistical analyses. Hospitals carefully must record data following strict guidelines, and tools should be implemented that allow quick information retrieval from the involved databases. Detailed and reliable data allow analysis of variance, which is essential for robust planning.


Figure 1: Seven steps to implement a Master Surgical Schedule

### 5.3. Capacity planning

Based on historical data and trends, capacity plans are made for every resource within the MSS scope. Capacity planning involves resource dimensioning and allocation within the constraints set by target production agreements, and agreements on utilization and availability of resources (Van Houdenhoven, et al., 2007a). It also involves reserving slack
time for dealing with the inherent variability of the process. There is a trade-off between utilization and robustness: reserving much slack time results in low utilization and high robustness against disruptions and overtime. To determine an acceptable amount of slack per resource, we recommend analyzing the effects of different capacity plans by 'what if' scenarios. Capacity plans should be adjusted accordingly.

Resources are allocated to specialists, specialties, or considered shared. The chosen type of allocation has consequences for the implementation of an MSS. Aside from the technical difficulties that arise when allocating to specialists, sharing resources might invoke resistance. As in most professional organizations, such as hospitals, professionals are organized in groups that are typically outside the control of the organization (Georgopoulos and Mann, 1962). This leads to distrust between specialists and managers regarding each other's intentions (Glouberman and Mintzberg, 2001a; b). Sharing resources, without clear allocation criteria, might lead to specialists refusing to cooperate. This may delay or even prevent implementation of an MSS.

### 5.4. Define a set of recurrent standard case types

An MSS is built up by a set of recurrent surgery types. Clustering techniques are used on the elective case mix (Bagirov and Churilov, 2003; Maruster, et al., 2002) to create a limited number of logistically and medically homogeneous surgery types. Examples of logistical characteristics are length of stay and surgery duration; examples of medical characteristics are diagnosis related groups and procedure codes. By periodically updating the set of recurrent surgery types (see Section 3.7), a hospital accounts for trends in data, for example seasonality in patient arrival and waiting lists. Aside from the standard surgery types for elective care, additional types are defined to cover emergency and semi-urgent patient mix.

The frequency of a surgery type in the MSS depends on the definition of the surgery type: the broader its definition, the less homogeneous it is but the higher its frequency will be. In addition, the broader the definition of the surgery type, the more the realization of the MSS will deviate from the initial schedule. The definition of the surgery types is thus a trade-off. We suggest the following iterative approach. First, given the initial definition of surgery types, each surgery type's frequency is calculated from historical demand and production data. These frequencies are proportionally adjusted to the MSS cycle length, and rounded down. The remaining fractions of surgery types are clustered (based on medical and logistical properties) into a small number of broad defined / dummy surgery types. Ideally, only a small proportion of the case mix is covered by these broad defined surgery types. If their proportion is too large, the definition of the initial surgery types is broadened, and the procedure is repeated. This approach should be repeated for different appropriate MSS cycle lengths to reach an optimum.

The organization may impose restrictions on the surgery type clustering. Management may e.g. impose that the MSS cycle length is aligned with the cycle of the roster of the involved personnel. Also, surgery type clustering is complicated if it takes place on the level of individual surgeons, instead of specialties.

### 5.5. Construction of the Master Surgical Schedule

The surgery types for emergency, semi-urgent and elective care are scheduled in an MSS such that the workload of involved resources is leveled, utilization is optimized, overtime is minimized, and emergency and semi-urgent surgery type waiting time is minimized (Van Houdenhoven, et al., 2007c; van Oostrum, et al., 2008), subject to various hard and soft constraints. Too many soft constraints that stem from personal preferences impact the quality of the resulting schedule. We refer to van Oostrum et al. (2008) for an advanced approach for constructing an MSS.

### 5.6. Execute the Master Surgical Schedule

For the execution of an MSS, a hospital should develop operational scheduling rules for three groups of patients, i.e., (1) emergency patients, (2) semi-urgent patients, and for patients who require elective surgery (3). Scheduling of emergency patients (1) in an MSS approach is no different than in other scheduling approaches, although we recommend not using a dedicated emergency OR (Wullink, et al., 2007). Regarding scheduling rules for semi-urgent patients (2) we suggest scheduling patients based in an earliest due date sequence (Dexter, et al., 1999a). Elective surgeries (3) can be planned by either surgeons or by an administrative department. In the latter case, input regarding the medically safe waiting interval is required. Assignment of elective patients is subject to the following guidelines:

- Assignment is allowed within the patient's medically safe interval and the planning horizon;
- Patients are assigned to the most appropriate surgery type slot, on a first come first serve basis, and as early as possible;
- Re-assigning patients is not allowed during the time required to make preparations for surgery (e.g. material coordination).
The selection of the length of the planning horizon is a trade-off between utilization and waiting time. The longer the planning horizon, the higher the utilization might become, since more possibilities for assigning patients to appropriate slots exist. However, some patients' waiting times might become longer than acceptable since they are postponed to surgery types at the end of the planning horizon, while they would have been assigned to dummy surgery types in case of a short planning horizon.


### 5.7. Update a Master Surgical Schedule

As long as the access times for all surgery types are balanced, the MSS needs no revision. However, access times change continuously under influence of seasonality in demand and changes in case mix characteristics such as new surgery types. The access times thus need to be monitored regularly, and the MSS should be revised if necessary. Performing a revision of an MSS holds all previous steps, with the only exception that the current MSS is taken as a start. Deviation from the previous MSS is to be minimized to reduce organizational effort related to an MSS update.

## 6. Thesis outline

In Chapters $2-5$ we present models that are required in a master surgical scheduling approach. Chapter 6 presents both theoretical prerequisites for implementation of master surgical scheduling in practices and practical lessons learned of the successful implementation in an acute general hospital. Chapter $7-9$ provides insight in how to deal with emergency patients in operating room departments. The chapters are written such that they can be read independently of each other. Therefore, each chapter starts with an abstract and an introduction.

Chapter 2 proposes a method to determine the costs of organizational constraints in operating room departments. These constraints concern the refusal of surgical departments to share operating room capacity. Analysis presented in this thesis shows how to objectively calculate the costs by means of mathematical programming techniques. Based upon the results of such calculations, a hospital can decide whether or not to take away organizational constraints. Such decisions affect the prerequisites under which a master surgical scheduling approach is developed in a particular hospital.

Chapter 3 deals with constructing basic surgery types. These surgery types function as building blocks for the master surgical schedule. Our aim is to construct surgery types that are medically and logistically homogenous. A modified version of Ward's hierarchical cluster method is proposed to do so. The proposed mathematical programming technique is tested on a case of an acute hospital, which has led to satisfactory results. The results give insights into the trade-off between variability in resource usage of surgery types and their fit into a master surgical schedule.

Chapter 4 considers the construction of the actual master surgical schedules. The problem comprises of scheduling surgery types, as can be constructed by the method proposed in Chapter 3, such that operating room utilization is maximized and bed usage is leveled. In this thesis a two-phase approach is proposed in which at first operating roomdays are constructed by a column generation heuristic. Operating room-days represent a set of surgery types that can be performed in a single operating room on a single day. In a second phase an integer linear programming model is solved to assign these operating
room-days to a master surgical schedule cycle such that bed usage is leveled. Computational experiments show that the two-phase approach works out well for both maximizing operating room utilization as well for bed usage leveling.

Chapter 5 evaluates the potential effect of using a master surgical schedule in a large university hospital and a large acute hospital in terms of increased operating room utilization and leveled bed occupancy. Both hospitals substantially benefit, but the acute hospital benefits more than the university hospital due to patient-mix characteristics. This chapter also discusses managerial advantages of using a master surgical schedule compared to other planning and scheduling approaches in hospitals.

Chapter 6 discusses that hospitals differ in size and organizational structure. This has implications for the applicability of master surgical scheduling. Using operations management as starting point the thesis evaluates potential implementation problems of master surgical scheduling in different types of organization. We conclude that the different organizational forms of hospitals have impact, but that the suggested master surgical scheduling concept is sufficiently flexible to be applicable in any of the organizational hospital forms. This has been investigated by implementation of the suggested master surgical scheduling approach in Beatrix hospital.

Chapter 7 presents a case study on the full service guarantee that Erasmus MC aims to give its surgical patients. This means that all elective surgical patients are treated on their scheduled date. Service guarantee is given to patients scheduled at schedules that adhere to organizational rules. Discrete-event simulation shows the effects on utilization, overtime, and number of cancellations when all patients receive service guarantee given that a certain number of operating room schedules fulfill the scheduling rules.

Chapter 8 deals with the issue of using a dedicated emergency operating room or not. This is an important issue for surgeons and plays an important role in discussions in scientific medical journals (see appendix to Chapter 8). Analysis shows for a large university hospital that having a dedicated emergency operating room is not only inefficient, but that it also increases emergency patient waiting times. The improved flexibility in operating room departments that allocate capacity for emergency surgery to all operating rooms is the major reason of the surprising results.

Chapter 9 considers the problem of determining the optimal size of emergency teams on call in the operating room during nights. The study explicitly uses so-called safety intervals for emergency patients. These safety intervals denote the time by which an emergency case can be delayed without causing increased morbidity and decreased probability of full recovery. By a discrete-event simulation model it is shown that staffing levels can be further reduced compared to other existing approaches when safety intervals are adopted.

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## Chapter 2

## Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical case scheduling

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## Chapter 2

# Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical case scheduling 

Abstract


#### Abstract

BACKGROUND: An operating room (OR) department has adopted an efficient business model and subsequently investigated how efficiency could be further improved. The aim of this study is to show the efficiency improvement of lowering organizational barriers and applying advanced mathematical techniques. METHODS: We applied advanced mathematical algorithms in combination with scenarios that model relaxation of various organizational barriers using prospectively collected data. The setting is the main inpatient OR department of a university hospital, which sets its surgical case schedules 2 wk in advance using a block planning method. The main outcome measures are the number of freed OR blocks and OR utilization. RESULTS: Lowering organizational barriers and applying mathematical algorithms can yield a $4.5 \%$ point increase in OR utilization ( $95 \%$ confidence interval $4.0 \%-5.0 \%$ ). This is obtained by reducing the total required OR time. CONCLUSIONS: Efficient OR departments can further improve their efficiency. The paper shows that a radical cultural change that comprises the use of mathematical algorithms and lowering organizational barriers improves OR utilization.


## 1. Introduction

Optimal use of scarce and expensive facilities such as operating rooms (ORs) requires efficient planning. The Erasmus University Medical Center (Erasmus MC), Rotterdam, The Netherlands, developed an OR business model based on controlled surgical case scheduling and management contracts. Nevertheless, OR department managers still explore new ways to improve OR efficiency.

The main inpatient OR department in Erasmus MC is run as a facilitating department that provides staffed and fully equipped ORs for the various surgical departments. A block planning approach has been adopted in which blocks of OR time are made available to surgical departments in advance (1,2). Departments may only assign patients to OR blocks that were made available to them. Regrettably, these organizational barriers result in suboptimal use of OR time. The OR business model furthermore incorporates the annual management contracts specifying the yearly amounts of OR time available for each surgical department. Capacity for emergency cases and uncertainty of case durations is accounted for by determining target OR utilizations for each surgical department independently. Any surgical case schedule, therefore, must include free OR
time, or "planned slack." Since target utilizations differ, planned slack also differs among surgical departments.

In summary, for the planning of surgical cases the surgical departments must adhere to the following rules:

1. Submit elective case schedules 2 wk in advance;
2. Maximize use of OR time and not exceed block times;
3. Plan elective cases using historical mean case durations;
4. Include planned slack to deal with emergency cases and variability of case durations.
Provided these rules are adhered to, the OR department "guarantees" that all scheduled surgical cases and emergency cases will be performed, whatever happens during the day. Moreover, applying these rules consequently helps surgical departments in their yearly contract negotiations about OR time with the hospital board.

The hypothesis to be tested was: combining advanced mathematical algorithms with lowering of organizational barriers among surgical departments improves OR efficiency. Several methods to improve efficiency have been proposed in the literature. Strum et al. (3) reported a benefit of approaching the OR planning problem as a newsvendor problem. Dexter et al. (4) recently showed the benefits of various approaches to surgical case scheduling. A broad overview of relevant literature is presented by McIntosh et al. (5). Mathematical algorithms to optimize surgical case schedules is a widely researched topic $(3,6-8)$. Several studies addressed the application of bin packing techniques, such as the Best Fit Descending heuristic $(9,10)$ or Regret-Based Random Sampling (RBRS) (11), yet within single departments. Finally, there is evidence that approaching the OR scheduling problem as a portfolio problem (12) may deal with the unpredictability of case durations and improve efficiency (11). Similar portfolio techniques are already in use for case mix management problems $(13,14)$.

Given the business model used by the main OR department of Erasmus MC, efforts are still focused on improving the current OR utilization. The aforementioned mathematical methods were examined. In addition, we report a computer simulation study assessing promising methods for creating efficient surgical schedules within scenarios that represent various degrees of lowering organizational barriers.

## 2. Methods

### 2.1. Data

Erasmus MC is a university hospital and tertiary referral center in Rotterdam, The Netherlands. Erasmus MC has 1237 beds and admits 34,500 patients per year, $60 \%$ $70 \%$ of whom undergo operation. The main inpatient OR suite consists of 16 ORs,

| Unit 1 | Unit 2 | Unit 3 | Unit 4 |
| :--- | :--- | :--- | :--- |
| Ear-nose-throat | General surgery | Oral surgery | Gynecological |
| surgery |  |  | surgery |
| Neurosurgery |  | Trauma | Urology |
| Ophthalmology |  | Orthopaedic |  |
|  |  | surgery |  |
| Plastic surgery |  | Plastic surgery |  |

Table 1: Clustering of 10 Erasmus Medical Center Surgical Departments into four units
providing the complete spectrum of surgical cases, including transplantation and trauma surgery. Organizationally, the Erasmus MC inpatient OR department is subdivided into four units, each serving a set of specialties (Table 1). Prospective data, approved immediately after the surgical procedure, are available for more than 180,000 surgical cases since 1994. Data on expected and real case durations and variations in durations for the 10 largest surgical departments were retrieved. Based on frequency, mean duration, and standard deviation of case duration, data were classified into four to eight homogeneous categories per surgical department (Table 2). Table 3 shows the OR suite fixed weekly block plan. All OR blocks in this study consisted of 450 min .

### 2.2. Mathematical representation of Erasmus MC's surgical case scheduling

Surgical case scheduling involves finding the combination of surgical cases that makes optimal use of available OR time. In the field of applied mathematics, this problem is known as the bin-packing problem. Currently, surgical departments schedule their surgical cases using a First-Fit approach (15). Searching from the beginning, patients are selected from a waiting list and scheduled in the first available OR in a particular week.

In our study, waiting lists were generated based on different surgical case categories representing each department's case mix (Table 2). Subsequently, a First- Fit algorithm simultaneously selected and scheduled surgical cases for the period of 1 wk which, in practice, is done approximately 2 wk before the date of surgery. This algorithm scheduled next cases only if the previous surgical case had been scheduled and if the algorithm concluded that it was impossible to fit the previous case into any of the available OR blocks. If the case did not fit in any of the available blocks, it was placed back on the waiting list. The algorithm terminates once it reaches the end of the waiting list. Note that for scheduling of cases the mean duration was used and that no planned overtime was allowed, as prescribed by the Erasmus MC rules. The resulting surgical case schedules comprised surgical cases, planned slack, and unused OR capacity (Fig. 1).

|  | General surgery |  | $\begin{gathered} \hline \text { Gynecological } \\ \text { surgery } \\ \hline \end{gathered}$ |  | Plastic surgery |  | Ear-nose-throat surgery |  | $\begin{gathered} \hline \text { Orthopedic } \\ \text { surgery } \\ \hline \end{gathered}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Cat. | $\begin{gathered} \text { Mean }^{a} \\ \text { (SD) } \end{gathered}$ | Freq. <br> (\%) | Mean (SD) | Freq. <br> (\%) | Mean (SD) | Freq. <br> (\%) | Mean <br> (SD) | Freq. <br> (\%) | Mean (SD) | Freq. <br> (\%) |
| 1 | 150 (89) | 8 | 80 (65) | 2 | 119 (107) | 5 | 102 (125) | 4 | 107 (58) | 9 |
| 2 | 67 (31) | 3 | 52 (19) | 14 | 63 (22) | 14 | 40 (17) | 33 | 61 (23) | 10 |
| 3 | 100 (44) | 12 | 73 (33) | 19 | 82 (28) | 17 | 65 (24) | 19 | 83 (30) | 18 |
| 4 | 135 (52) | 19 | 98 (32) | 25 | 112 (36) | 21 | 102 (35) | 12 | 109 (38) | 21 |
| 5 | 171 (63) | 20 | 125 (43) | 32 | 139 (39) | 22 | 127 (32) | 14 | 160 (43) | 21 |
| 6 | 213 (89) | 3 | 156 (41) | 2 | 187 (57) | 11 | 182 (65) | 8 | 199 (45) | 16 |
| 7 | 262 (87) | 25 | 213 (82) | 6 | 432 (181) | 10 | 254 (75) | 5 | 291 (102) | 5 |
| 8 | 351 (124) | 9 |  |  |  |  | 549 (203) | 6 |  |  |
|  | Urology |  | Trauma |  | Ophthalmology |  | Neurosurgery |  | $\begin{gathered} \text { Oral } \\ \text { surgery } \end{gathered}$ |  |
| Cat. | Mean <br> (SD) | Freq. <br> (\%) | Mean <br> (SD) | Freq. (\%) | Mean <br> (SD) | Freq. (\%) | Mean (sD) | Freq. (\%) | Mean <br> (SD) | Freq. (\%) |
| 1 | 121 (68) | 3 | 100 (68) | 7 | 83 (46) | 1 | 192 (165) | 8 | 97 (37) | 1 |
| 2 | 59 (30) | 5 | 62 (23) | 22 | 46 (14) | 35 | 113 (41) | 17 | 87 (29) | 44 |
| 3 | 74 (26) | 30 | 81 (30) | 32 | 60 (22) | 42 | 171 (62) | 14 | 130 (43) | 44 |
| 4 | 102 (49) | 15 | 122 (38) | 20 | 95 (30) | 17 | 255 (62) | 28 | 238 (87) | 11 |
| 5 | 152 (49) | 17 | 176 (92) | 19 | 127 (34) | 5 | 324 (73) | 12 |  |  |
| 6 | 230 (68) | 21 |  |  |  |  | 492 (177) | 21 |  |  |
| 7 | 385 (123) | 8 |  |  |  |  |  |  |  |  |

Cat. $=$ category; SD = standard deviation; Freq. = frequency.
Sample sizes: General surgery 31,209 , gynecological surgery 10,163 , plastic surgery 14,318 , ear-nose-throat surgery 17,103 , orthopedic surgery 11,859 , urology 11,876 , trauma 8385 , ophthalmology surgery 9801 , neurosurgery 10,370 , and oral surgery 2608 . Surgical cases were classified based on their expected duration. Surgical cases for which no prediction of the case duration was available are grouped in Category 1.
$a$ Mean and standard deviation (SD) are given in minutes.
Table 2: Characteristics of the 10 main surgical departments in Erasmus Medical Center. Each category represents the patient mix for a department

| Specialty | No. Of Operating rooms per day of the week |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Mon | Tue | Wed | Thu | Fri |  |
| General surgery | 3 | 3 | 3 | 3 | 3 |
| Gynecological surgery | 1 | 1 | 1 | 1 | 1 |
| Oral surgery | 1 | 1 | 1 | 1 | 1 |
| Ear-nose-throat surgery | 2 | 2 | 2 | 1 | 2 |
| Neurosurgery | 2 | 2 | 2 | 2 | 2 |
| Trauma | 1 | 1 | 0 | 1 | 1 |
| Ophthalmology | 1 | 1 | 1 | 1 | 1 |
| Orthopedic surgery | 1 | 1 | 2 | 1 | 2 |
| Plastic surgery | 2 | 2 | 2 | 2 | 1 |
| Urology | 2 | 2 | 2 | 2 | 2 |

Table 3: Fixed weekly block plan for the inpatient operating room department of Erasmus medical center with 16 operating rooms

### 2.3. Planned slack and the portfolio effect

The financial world deals with uncertainty by using the portfolio effect. This ensures that the expected return of a stock portfolio is less vulnerable to fluctuations on the stock market. The term "portfolio effect" then indicates that portfolio risk decreases with increasing diversity, as measured by the absence of correlation (covariance) between portfolio components (16). We earlier found application of the portfolio effect to surgical case scheduling to be successful in increasing $O R$ efficiency, since it reduces the required amount of planned slack, given an accepted risk of overtime (11). The approach clustered surgical cases with similar variability in the same OR block, assuming these to be uncorrelated.

We illustrate the portfolio effect applied to surgical case scheduling by the following example: Consider two OR


Figure 1: Graphical representation of a surgical case schedule, which typically includes various surgical cases, planned slack, and unused operating room time.


Figure 2: Example of planned slack reduction as a result of the portfolio effect. The sum of the shaded areas in the two operating room blocks on the left exceeds that in the two operating room blocks on the right.
blocks, both of which have two surgical cases scheduled. One case with (mean, standard deviation $)=(100,10)$ and one case with (mean, standard deviation $)=(100,50)($ Fig. 2) (all values are given in minutes). We assumed that case durations are described by a normal distribution function. In this example, we now compared this situation (the left side of Fig. 2) with the situation in which surgical cases with similar variance are clustered. In the first situation, the standard deviation of total duration is the same for both OR blocks: $\sqrt{ }\left(50^{2}+10^{2}\right)=51.0 \mathrm{~min}$. The total planned slack for the two blocks is thus $102.0 \beta \mathrm{~min}$, where $\beta$ is a risk factor to deal with risk of overtime. Since the sum of the durations follows a normal distribution the following holds: $P($ mean $+\beta$ standard deviation $) \sim$ accepted risk of overtime, such that given a certain accepted risk of overtime the risk factor can be calculated. In the second situation, the total planned slack is: $\left(\sqrt{ }\left(50^{2}+50^{2}\right)+\sqrt{ }\left(10^{2}\right.\right.$ $\left.\left.+10^{2}\right)\right) \beta=84.9 \beta \mathrm{~min}$. This means a $17.1 \beta \mathrm{~min}$ reduction in the total required planned slack time, and thus an equal increase in available capacity. This portfolio profit will increase with higher variability of the cases concerned. This example illustrates that rescheduling a surgical case can reduce the extent of planned slack.

### 2.4. Organizational barriers

We constructed three scenarios to investigate the impact of lowering organizational barriers imposed by block planning (Table 4). The scenarios are graded as to interdepartmental flexibility (i.e., scheduling cases of different departments in the same OR on 1 day) and flexibility of rescheduling surgical cases between days of the week compared with the current situation. Rescheduling of surgical cases throughout the week does not affect patients, since they have not yet been scheduled.

In this study, we assumed application of the scenarios directly after the construction of the surgical case schedules, approximately 2 wk before the actual execution of the schedule (Fig. 3). This enables OR departments to take necessary steps to ensure feasibility; for example regarding material logistics, ranging from specific surgical material to complete navigation system for complex craniotomy

| Scenario | Interdepartmental flexibility | Flexibility over the week |
| :---: | :---: | :---: |
| 1 | OR block consists of surgical cases of a <br> single department | Rescheduling on the same day |
| 2 | OR block consists of surgical cases of a <br> single department | Rescheduling within the same week |
| 3 | OR block consists of surgical cases of a <br> department within one unit | Rescheduling on the same day |

See Table 1 for the clustering of surgical departments in organizational units. The flexibility is applied to the construction of surgical schedules 2 wk in advance. $\mathrm{OR}=$ operating room.

Table 4: Description of scenarios representing various flexibility levels
surgery. Surgical departments are responsible for the scheduling of semi-urgent or add-on elective patients who need an operation on a day for which a surgical case schedule is already set. For this purpose, departments may schedule cases without assigning a patient to it, or by canceling one or more of the elective cases. Emergency patients are operated on within the reserved OR time as described earlier.

### 2.5. Advanced mathematical algorithms

Application of the different scenarios to a surgical case schedule implied rescheduling of surgical cases according to the organizational flexibility of the scenario under consideration. A bin-packing algorithm, based on work of Hans et al. (11), who used RBRS, did the rescheduling of the surgical schedules given the scenarios. Figure 4 shows how rescheduling surgical cases saves OR time. The objective of the algorithm is to minimize planned slack by exploiting the portfolio effect and the required number of OR blocks. RBRS procedures start with removing all cases of the existing surgical schedule to a list. Then, RBRS iteratively schedules a random surgical case from the list until all cases are scheduled. The drawing probability of each of the cases is based on the case's Best Fit suitability. This randomized procedure gives a new solution (a "surgical case") every time it is executed. We stopped the algorithm after generating a preset number of 1500 surgical case schedules. The generated schedules were evaluated on the objective criterion (amount of free OR capacity) and the best schedule was saved (11). The algorithm was coded in the Borland Delphi computer language (Cupertino, USA).

### 2.6. Experimental design

The Erasmus MC's main inpatient department considered using the news-vendor approach of Strum et al. (3). Subsequently, we investigated the benefits of the RBRS that exploited the portfolio effect and relaxation of the organizational constraints. To this aim, the surgical case scheduled created by the RBRS algorithm was compared with the surgical schedules constructed by the First-Fit approach. The RBRS algorithm was compared with the Best Fit algorithm (7) to assess the performance of advanced mathematical algorithms over available and simpler heuristic techniques.

We performed a robustness analysis on the influence of unpredictability of case duration on OR utilization, wherein the unpredictability was represented by the standard deviation of case duration. The influence of number of ORs within an OR department on OR utilization was investigated as well. Both analyses were performed for each of the three flexibility scenarios. The outcome measures of this study are OR utilization and the number of freed OR blocks, so- called "freed ORs." OR utilization was defined as the ratio between the total duration of elective surgical cases and the total staffed OR capacity per week. Hence, it is similar to what is known in the literature as "raw OR utilization" (17).


NB. Information on the mean duration and variability of duration is available for all surgical cases at all stages.
Figure 3: Positioning of the operating room scheduling process. The focus of this paper is on scheduling surgical cases approximately 2 wk in advance, methodology for scheduling add-on and elective cases is beyond the scope of this paper and therefore not explicitly described in the figure.


Spec. 1: General Surgery
Spec. 2: Eye Surgery
Spec. 3: Plastic Surgery
Spec. 4: Trauma
Spec. 5: ENT
Figure 4: Example of creating a free operating room block by reallocating surgical cases.

## 3. Results

Applying the news-vendor approach of Strum et al. (3) did not lead to improved efficiency. With staffing costs determined by the allocated capacity and overtime by a relative cost ratio of 1.5 and increasing the block times with 15 min , it even decreased efficiency (Table 5). Therefore, new ways to increase OR efficiency were explored, as described in the previous section.

Increased flexibility in the three scenarios increased the number of freed OR blocks (Table 6). Eventually, this resulted in an improved utilization rate of $4.5 \%$ points ( $95 \%$ confidence interval $4.0 \%-5.0 \%$ ). Both the Best Fit Descending heuristic and the RBRS algorithm improved utilization. The latter, more advanced, algorithm significantly out-performed the first heuristic by $0.7 \%$ point in Scenario 2 ( $95 \%$ confidence interval $0.2 \%-1.2 \%)$. Applying either the RBRS algorithm or the Best Fit Descending did not significantly improve the initial surgical schedules when combined with Scenario 1 (i.e., blocks consists of surgical cases of a single department and cases are rescheduled on the day). No significant difference was measured between the Best Fit Descending heuristic and the RBRS algorithm in Scenario 1 (Table 6).

|  | Standard <br> deviation (min) |  |  |
| :--- | :---: | :---: | :---: |
| Mean (min) | Proportion (\%) |  |  |
| Under-utilization | 59 | 68 | 52 |
| Over-utilization | 40 | 94 | 47 |

Measures are based on 30 consecutive months from January 1, 2004 onwards.
Table 5: Operating room performance

|  | Current situation <br> Mean $\pm \mathrm{SE}$ <br> $(\%)$ | Scenario 1 <br> Mean $\pm \mathrm{SE}$ <br> $(\%)$ | Scenario 2 <br> Mean $\pm \mathrm{SE}$ <br> $(\%)$ | Scenario 3 <br> Mean $\pm \mathrm{SE}$ <br> $(\%)$ |
| :--- | :---: | :---: | :---: | :---: |
| First Fit case schedule | $77.4 \pm 0.2$ |  |  |  |
| RBRS algorithm |  | $77.5 \pm 0.2$ | $81.9 \pm 0.2$ | $78.8 \pm 0.2$ |
| Best Fit Descending <br> RBRS algorithm versus Best <br> Fit Descending |  | $77.4 \pm 0.2$ | $81.2 \pm 0.2$ | $78.2 \pm 0.2$ |

Utilization is defined as the ratio between the total amount of elective surgical cases and the total allocated OR capacity. $\mathrm{SE}=$ standard error. Mean and $95 \%$ confidence interval (CI) of differences between Regret-Based Random Sampling (RBRS) algorithm and Best Fit Descending in the three scenarios are examined by a paired $t$-distribution.
" Mean (95\% CI) (\%).
Table 6: Operating room (OR) Utilization rates


Figure 5: Graphic representation of the number of freed operating room blocks in Erasmus Medical Center when the Regret-Based Random Sampling algorithm is applied in combination with the three scenarios in which the standard deviation of case

Number of freed OR blocks, and hence OR utilization, increased relative to the standard deviation of case duration within one department (Fig. 5). The RBRS algorithm and the portfolio effect did not significantly improve the original schedule in Scenario 1, regardless of the standard deviation in the patient mix. Furthermore, in Scenarios 2 and 3, the benefits of the RBRS algorithm increased with the standard deviation of case duration.

Figure 6 shows the association between number of ORs and OR utilization rate expressed in number of freed OR days for the three scenarios. The findings shows that if more flexibility would be achievable, benefits progressively increase with the number of cases performed daily relatively to the available hours provided.


Figure 6: Graphic representation of the number of freed operating room blocks when the Regret-Based Random Sampling algorithm is used in combination with the three scenarios for operating room departments of various sizes.

## 4. Discussion

The study showed how to improve OR efficiency by combining advanced mathematical and financial techniques with the lowering of organizational barriers. The combination facilitates OR departments to improve OR efficiency when current methods will no longer benefit ( 3,7 ). The method is applicable in hospitals that set their surgical case schedules approximately 2 wk in advance, and potentially improves OR utilization by $4.5 \%$. Improved efficiency implies that more operations can be performed at the same OR capacity or that less OR capacity is needed for the same number of operations. We also showed that potential benefits vary for different OR departments, depending on the uncertainty in case duration and number of ORs within one OR department. Absolute measures of this study are difficult to compare with results from other studies because Erasmus MC uses a specific method of reserving OR time in surgical schedules.

The algorithms used aimed to free OR blocks, because capacity that was previously allocated in these blocks is not accounted for while calculating the utilization rate. This is true for all OR departments that have sufficient flexibility in their staff scheduling to allow changes approximately 2 wk in advance.

We assumed in the analysis that surgical case durations show normal distribution. Other studies have shown that a lognormal distribution is a better approximation of the real duration (18). Calculation of planned slack, which is required to simulate the portfolio effect, requires a closed form probability distribution. This is not the case for a lognormal distribution, and this is why we have opted for a normal distribution, which may modestly influence the outcomes. Since the amount of planned slack is similarly calculated for the RBRS algorithm compared with that for the Best Fit heuristic, we do not expect that the assumption influences the calculated outcomes.

Many hospital use information technology systems to actually schedule their surgical cases in the available blocks. The mathematical techniques presented in this paper can easily be incorporated in such information technology systems, permitting planners to actually use the mathematical algorithms. Using the techniques addressed in this paper, and given a flexibility scenario agreed upon beforehand, the set of cases planned by the different departments in their blocks is collectively optimized after surgeons have set their patients' surgery dates. After optimization, each department can match its surgeon and bed planning with the new, more efficient, case schedule.

Lowering organizational barriers might have some negative effects and will require a more flexible attitude of surgical departments and individual surgeons. First, allowing various surgical departments to use the same OR may result in longer waiting times for surgeons. Second, surgeons may be scheduled in various ORs on the same day. Third, having surgeons operate on different days in the week requires adjustment of their other tasks, especially in hospitals where surgeons are highly specialized and where cases cannot be interchanged among surgeons. All these issues should be carefully addressed and
weighed against the efficiency increase. The essential consideration, we believe, is that the drawbacks for a surgical department can be compensated for by the huge amount of extra OR capacity, which can be used to shorten the waiting list and earn more money.

Another aspect of implementation of the techniques is the required additional flexibility of the ORs. Each OR has to be uniformly equipped so that all surgical departments may operate in it. The efficiency increase achieved by the proposed method would justify the investment to equip all ORs generically.

Each hospital can choose a flexibility scenario that matches its requirements. Even more scenarios can be made to show benefits of even lower organizational barriers. The potential benefits can be calculated by comparing the current case scheduling strategy, in this paper represented by a first-fit algorithm, and the future situation in which the portfolio effect and bin-packing techniques have been applied and organizational constraints have been relieved. This paper provides a tool for any hospital type to make their own trade-off between flexibility and higher utilization of OR capacity.

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## Chapter 3

## A method for clustering surgical cases to allow master surgical scheduling

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## Chapter 3

# A method for clustering surgical cases to allow master surgical scheduling 

Abstract

Master surgical scheduling can improve manageability and efficiency of operating room departments. This approach cyclically executes a master surgical schedule of surgery types. These surgery types need to be constructed with low variability to be efficient. Each surgery type is scheduled based upon its frequency per cycle. Surgery types that cannot be scheduled repetitively are put together in so-called dummy surgeries. Narrow defined surgery types, with low variability, lead to many of such dummy surgeries, which reduces the benefits of a master surgical scheduling approach. In this paper we propose a method, based on Ward's hierarchical cluster method, to obtain surgery types that minimize the weighted sum of the dummy surgery volume and the variability in resource demand of surgery types. The resulting surgery types (clusters) are thus based on logical features and can be used in master surgical scheduling. The approach is successfully tested on a case study in a regional hospital.

## 1. Introduction

Hospitals are complex-structured organizations that are often hard to manage (5; 4). An operating room department is a typical example of a department where many different actors cooperate, which leads to a complex organizational situation. Moreover, hospitals consider operating room departments as the organization part that generates the most revenue and the most costs. Hence, manageability and the efficiency of this department is subject of a broad range of studies, see for examples ( $7 ; 1 ; 16$ ). A good overview of operating room planning and scheduling can be found in Cardoen et al. (2) and McIntosh et al. (11).

One approach to improve efficiency and manageability of operating room departments is the so-called master surgical scheduling approach ( $8 ; 14 ; 13$ ). It cyclically executes a master surgical schedule (MSS) of surgery types. An MSS allows not only for optimization of operating room utilization, robustness, and overtime, but it also takes resource demand on other departments such as wards into account. The surgery types in an MSS function as its building blocks. Based on their resource demand profiles the MSS is optimized (14; 13). Constructing surgery types with little variability in their resource demand is therefore preferred.

Newly arrived patients or patients from waiting lists are assigned to surgery types in an MSS on a weekly basis. To reduce the probability of non-assigned surgery types, the historical frequencies of the demand for a surgery types per week are rounded down to obtain the frequencies of surgery types that are allocated in the MSS. For example, when cataract surgery occurs on average 6.7 times per week, only 6 surgeries of the cataract type
are incorporated in the MSS. The remaining demand fraction will be allocated in so-called dummy surgery types. The positive effect of using an MSS is reduced when the volume of dummy surgeries becomes large. We therefore aim to construct a set of surgery types with a low volume of dummy surgeries as well as a low variability in demand usage.

In this paper we propose a method to obtain such a set of surgery types. We draw more elaborately the background of the problem in Section 2 and we formally introduce the problem in Section 3. In Section 4 we provide a brief summary of available method for clustering. Our suggested solution approach is presented in Section 5 and applied to a case study in Section 6. We conclude the paper in Section 7.

## 2. Background

An MSS is built from a set of recurrent surgery types. The problem at hand is to create a limited number of logistically and medically homogeneous surgery types. Examples of logistical characteristics are length of stay and surgery duration; examples of medical characteristics are diagnosis related groups and procedure codes. We assume that a previous period is representative for the coming period, both for the frequency of occurrence of surgical cases as for the variability in resource consumption by patients.

We focus on the construction of surgery types for the elective case mix. Aside from the standard surgery types for elective care, additional types can be defined to cover the emergency and semi-urgent case mix. The hospital organization may impose restrictions on the surgery type clustering. For instance, clustering might be done only within a surgical department as we assume in this paper.

The frequencies of surgery types are calculated as follows. Given historical data, surgery types are constructed as combination of one or more specific surgical cases. The surgical cases define the lowest level in the required data. Given a surgery type, and the historical demand for its underlying surgical cases, an average frequency per MSS cycle is calculated. Management may require that the MSS cycle length is aligned with other process cycles in the hospital such as personnel rostering. Furthermore a hospital may not be opened during all weeks. After obtaining an average frequency per MSS cycle, given its length and the total number of repetitions per year, the frequency is rounded down. The remaining fractions of surgery types are clustered into dummy surgery types. Clearly the volume of dummy surgery types depends on the definition of the surgery types. When a set consists of surgery types that are broadly defined, this tends to reduce the volume of dummy surgery types, but lead to higher uncertainty in the resource consumption of patients assigned to such a broadly defined surgery types than a situation where patients are assigned to narrowly defined surgery types. However, the latter may results in a substantial volume of dummy surgery types which is conflicting with the MSS approach. Ideally, only a small proportion of the case mix is covered by dummy surgery types.

An MSS aggregates the level of surgical scheduling from individual patients to patient types. The loss of information due to this aggregation (e.g., surgery duration will be less predictable) will be compensated by benefits inherent to the MSS approach (13). Using an MSS cyclically will improve manageability and will reduce weekly variation in bed occupancy compared to an operating room department that weekly constructs a surgical schedule from scratch. In the latter the hospital organization suffers from late information and peak demand. Still, when constructing surgery types, we aim to minimize the loss of information in the process of constructing surgery types.

## 3. Literature

Clustering problems and cluster analysis form a large research area. Also in the area of health care this topic is far from new. An excellent overview of existing techniques and their application in a health care setting is given by Dilts et al. (3). The complexity of clustering problems rapidly increases with the problem size (9). Therefore solution algorithms are often derived from available methods in the field of mathematical programming, see for example Hansen and Jaumard (6).

Algorithms to solve clustering problems are usually subdivided into hierarchical algorithms and non-hierarchical algorithms (e.g., partitioning algorithms) (3; 9). Constraints may be added to hierarchical methods to reduce the number of possible splits or merges. The optimal number of clusters does not need to be known beforehand. An investigator selects the best set of clusters after all different numbers of clusters are generated. Hierarchical cluster algorithms are either agglomerative or divisive in nature. Agglomerative hierarchical methods successively combine items closest to one another into a new cluster until one cluster is left. Divisive methods start with all items grouped in one cluster, and successively split off a set of items to form a new cluster. The divisive splitting is based on either one variable (monothetic) or upon multiple variables (polythethic).

Non-hierarchical methods generally start with an initial set of clusters. Based upon the definition of similarity/distance measure items are assigned to these clusters by some heuristic. Afterwards items may be reassigned to further optimize the clustering. The K-means method is one of the well known methods in this group of cluster algorithms. For a detailed overview of available clustering techniques and their application we refer to Dilts et al.(3), Romesburg (12), and Johnson and Wichern (9).

The need to classify patients to allow advanced planning and scheduling has also been acknowledged in the field of health care logistics, see for example Vissers et al. (15), who show how classification of patients can be used to improve hospital management using patient clustering as one of their building block in a logistical framework. Maruster et al. (10) show the application of clustering techniques to obtain logistic-based patient groups of patients treated for peripheral arterial vascular diseases. The authors show that
the resulting clusters support improved planning and control of patients to increase the efficiency of resources within hospitals.

## 4. Problem definition

We denote $Z$ as the set of all types of surgery, called surgical case, that are performed in the hospital by a surgical department, with $z \in Z$ a particular surgical case. Basically $z$ is the lowest level of registration in a hospital's database. Consider a hospital that wants to optimize utilization of resources $r=1, \ldots, R$ by means of an MSS, where $r$ can be for instance the operating room department or wards. These resources may vary in importance, for instance by their costs. Hence, to make the various resources comparable we scale $r$ by parameter $w_{r}$.

We perform the clustering of surgical cases based upon patient data of the previous period, hence we use post-classification. For reasons of simplicity and without loss of generality we assume that this period equals one year. Let $I$ be the set of all patients that are operated in that year. We denote their consumption of resource $r$, scaled by $w_{r}$, for patient $i$ by $X_{i r}$.

By clustering surgical cases $z \in Z$ we generate surgery types that are scheduled in an MSS. Hence, the surgery types are the outcome of the application of a clustering. We describe a particular surgery type by $c \in C$.

We introduce subset $I_{z}$ to denote all patients that were operated for surgical case $z$. Subset $Z_{c}$ denotes the surgical cases $z$ that are clustered to surgery type $c$. The MSS approach requires that all surgical cases are assigned to exactly one surgery type, therefore $Z^{c} \cap Z^{\bar{c}}=\varnothing$ for $c \neq \bar{c}$ and $\sum_{c \in C} Z^{c}=Z$.

Our problem now comprises of optimizing the clustering of surgical cases $z$ in surgery types $c$ such that the weighted sum of the volume of dummy surgeries and the variability within clusters is minimal. We concern variability in terms of the variation in demand per resource. The variability of a cluster of surgical cases is therefore a sum of the variability that occurs in resource demand of each of the separate resources. Minimizing this sum makes that we obtain logistically homogeneous clusters usable in an MSS. Clustering might be subject to additional constraints, as in our case surgery types are constructed per surgical department. A formal definition of the objective function is given in Section 5.

## 5. Solution approach

In our problem, as addressed in Section 1, the volume of dummy surgeries negatively influences the performance of an MSS. A large number of clusters/surgery types tends to lead to a high volume of dummy surgeries. Basically this makes that the number of surgery types cannot be determined in advance. Therefore hierarchical cluster methods fit our
problem better than nonhierarchical methods do, while we chose for reasons of complexity for an agglomerative approach (9). Furthermore, from a mathematical point of view the cost of the volume of dummy surgeries can be described by a step-wise cost function on the number of items in the clusters. To the best of our knowledge no other papers have been published that use such costs function in the context of clustering problems.

We aim to construct surgery types with a minimal loss of information compared to using individual surgical cases. This can be done by Ward's Hierarchical Clustering Method (17). We consider this method as most appropriate to use as a starting point for our solution approach.

### 5.1. Modeling volume of dummy surgeries

Assume that the available data concerns a period of one year without a trend that necessitates adjusting frequencies of surgical procedures in the upcoming period. We denote the length of a single MSS cycle by $T$ days and the number of repetitions per year by $A$. Note that in practice $T$ times $A$ is often smaller than a full year since hospitals have periods during a year, e.g. Christmas Holiday, where almost no elective surgery is performed. Hence, the volume of dummy surgeries that originates from surgery type $c$, as denoted by $\mathrm{v}_{\mathrm{c}}$, is calculated by rounding down the frequency per cycle and can be calculated as:

$$
\begin{equation*}
v_{c}:=\left(\bigcup_{z \in Z^{c}}\left|I^{z}\right|\right) \bmod A \cdot T \tag{1}
\end{equation*}
$$

### 5.2. Modeling resource demand variability

Putting two different surgical cases in one surgery type together leads to loss of information (regarding the resource consumption) compared to a situation where both procedure types are individually assigned to a surgery type. We base our solution approach on Ward's Hierarchical Clustering Method (17). This method uses the error sum of squares (ESS) as measure for the loss of information. Let $E S S_{c}$ be the error sum of squares of surgery type $c$, which is computed by

$$
\begin{equation*}
E S S_{c}:=\sum_{z \in Z^{c}} \sum_{i \in I^{Z}} \sum_{r \in R}\left(X_{i r}-\frac{\sum_{z \in Z^{c}} \sum_{i \in I^{z}} X_{i r}}{\bigcup_{z \in Z^{c}}\left|I^{Z}\right|}\right)^{2} \tag{2}
\end{equation*}
$$

Note that the different resource types $r$ in Formula 2 are already scaled in $X_{i r}$. The overall ESS is determined by the sum of the ESS per cluster: $E S S=E S S_{1}+E S S_{2}+\ldots+E S S_{C}$.

### 5.3. Solution heuristic

To cluster surgical cases into surgery types we propose a modified version of Ward's Hierarchical Clustering Method. The basic outline, which is similar to most agglomerative hierarchical clustering methods (3), of this method applied to our problem is the following:

1. Start with N surgery types $(|C|=|Z|=N)$, each containing a single surgical case type $z$ and an $N x N$ symmetric matrix of costs $\mathbf{D}=d_{c \tilde{c}}$
2. Search the distance matrix for the combination of surgery types with minimal costs. Let this combination consist of surgery types $c$ and $\tilde{c}$.
3. Merge surgery types $c$ and $\tilde{c}$. Rename the new surgery type as $c \tilde{c}$. Update the distance matrix by adding the new surgery type $c \tilde{c}$ and removing $c$ and $\tilde{c}$.
4. Record the intermediate set of surgery types and repeat Step 2, 3 and 4 until one surgery type remains $(|C|=1)$.
The elements of matrix $\mathbf{D}$ represent the additional costs of combining two surgery type compared to the current situation. This is calculated as follows:

$$
\begin{equation*}
d_{c \tilde{c}}:=k_{1}\left(v_{c \tilde{c}}-\left(v_{c}+v_{\tilde{c}}\right)\right)+k_{2}\left(E S S_{c \tilde{c}}-\left(E S S_{c}+E S S_{\tilde{c}}\right)\right) \tag{3}
\end{equation*}
$$

where $k_{1}$ and $k_{2}$ represent respectively the importance of the volume of dummy surgeries and the importance of the loss of information (increased variability).

The final step comprises of finding the best solution. Note that solutions correspond to a set of surgery types (clusters) in a particular step of the above procedure. The costs at such a step are calculated as follows:

$$
\sum_{c \in C}\left(k_{1} \cdot v_{c}+k_{2} \cdot E S S_{c}\right)
$$

Note that the optimal solution is not necessarily the initial solution, where the ESS is at a lowest level, or the final solution, where the volume of dummy surgeries is at the lowest level. The solution with the lowest costs gives the best set of surgery type according to the criteria defined in the problem definition. However, not all practical restrictions are incorporated in our solution approach. Therefore, some surgery types may be split in practice.

## 6. Case study

In this section we are concerned with the construction of surgery types for Beatrix Hospital, the Netherlands. Beatrix hospital is a regional hospital for primary hospital care. There are 5 inpatient and 3 outpatient operating rooms. The hospital has approximately 329 beds. Beatrix hospital currently implements the MSS approach as described by Van Oostrum et al. (13). Using an MSS, it aims to optimize operating room utilization and to improve the leveling of ward occupancy. As part of this implementation, the clustering techniques as described in Section 5 were used to propose surgery types for the MSS. The
experiments were performed by the solution heuristic (Section 5) coded in MathLab version 7.0.

### 6.1. Data

To construct surgery types we obtained data of all elective surgical inpatients that were operated in 2006. From each patient we obtained, among other data, their surgical procedures, their length of stay (LOS) in the hospital, and their surgery duration (SurDur) ( $r \in\{L O S, S u r D u r\}$ ). Surgical data was registered in the operating room by nurses and retrospectively approved by surgeons. LOS data was registered by nurses at wards for financial purposes.

To scale the resource variables, Beatrix hospitals assumes that one day admission equals one hour of operating room time in costs ( $w_{\text {LOS }}=1, w_{\text {SurDur }}=160$ ). Beatrix hospital considers implementation of an MSS with a length of either one or two weeks ( $T=1$ or 2 ). The operating room department runs on an annual basis during a period equivalent with 46 weeks $(A=46)$. Table 1 presents a summary of the Beatrix hospital data. In the first column all seven surgical departments are given. The second column presents the total number of patients (set $I$ ), while the third column presents the total number of different surgical cases $(z=1, \ldots, Z)$. We solve the cluster problem in Beatrix hospital for each surgical department separately.

We vary the parameter values $k_{1}$ and $k_{2}$ indicating the importance of the volume of dummy surgeries relative to the loss of information. We take as values $k_{1}=\{0,0.5,1,5,10,20\}$ and keep $k_{2}$ constant at $k_{2}=1$.

| Surgical |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| department | Number of <br> patients | Number of <br> surgical <br> cases | Mean <br> surg. dur. <br> (minutes) | Std. dev. <br> surg. dur. <br> (minutes) | LOS <br> (days) | LOS <br> (days) |
| General surgery | 1428 | 153 | 72 | 56.2 | 2.7 | 4.7 |
| Gynecology | 783 | 47 | 57 | 43.8 | 2.3 | 2.4 |
| ENT | 1432 | 42 | 27 | 29.8 | 1.2 | 0.8 |
| Eye surgery | 1194 | 24 | 29 | 10.3 | 1.0 | 0.6 |
| Orthopedic | 1751 | 89 | 47 | 37.5 | 2.2 | 3.0 |
| surgery | 369 | 20 | 39 | 25.3 | 1.6 | 3.2 |
| Plastic surgery | 34 | 53 | 71 | 68.6 | 3.4 | 2.7 |
| Urology | 434 | 7391 | 428 | 47 | 44.1 | 2.0 |
| Overall |  |  |  |  |  | 2.9 |

Table 1: Overview patient mix data Beatrix Hospital in 2006. Surg. dur. = surgery duration, Std. dev. $=$ standard deviation, and LOS $=$ Length of stay

### 6.2. Case study results

Table 2 presents the number of surgery types resulting after application of our solution heuristic. As can be expected the number of resulting surgery types equals the number of different case types in the data when $k_{2}=0$ is taken. However, when $k_{2}>0$ is taken the number of different surgery types sharply declines. Table 3 shows the increase in the loss of information (ESS) and the volume of dummy surgeries. This data can be visualized to determine the best trade-off between ESS increase and the volume of dummy surgeries, see for an example Figure 1. It is clear that obtaining the lowest volume of dummy surgeries lead to a high increase in ESS and contrarily that the lowest increase in ESS causes a high volume of dummy surgeries.

|  |  | k 1 |  |  |  |  |  |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: | ---: |
|  |  | 0 | 0.5 | 1 | 5 | 10 | 20 |
| $\mathrm{~T}=1$ | General surgery | $152-153$ | 31 | 40 | 13 | 13 | 13 |
|  | Gynecology | 47 | 14 | 14 | 5 | 2 | 2 |
|  | ENT | 42 | 15 | 15 | 6 | 1 | 1 |
|  | Eye surgery | $22-24$ | 10 | 10 | 10 | 10 | 10 |
|  | Orthopedic surgery | $86-89$ | 17 | 17 | 5 | 6 | 6 |
|  | Plastic surgery | 20 | 16 | 6 | 6 | 1 | 1 |
|  | Urology | 53 | 22 | 13 | 13 | 13 | 5 |
| $\mathrm{~T}=\mathbf{2}$ | General surgery | $152-153$ | 40 | 42 | 18 | 20 | 11 |
|  | Gynecology | 47 | 16 | 13 | 7 | 5 | 5 |
|  | ENT | 42 | 7 | 7 | 10 | 10 | 3 |
|  | Eye surgery | $22-24$ | 5 | 5 | 5 | 5 | 5 |
|  |  |  |  |  |  |  |  |
|  | Orthopedic surgery | $86-89$ | 29 | 19 | 7 | 7 | 7 |
|  | Plastic surgery | 20 | 7 | 7 | 7 | 2 | 2 |
|  | Urology | 53 | 22 | 23 | 15 | 15 | 15 |

Table 2: Number of surgery types in the best solution found for different values of $k_{1}$. Multiple solutions are denoted as a range.

Chapter 3

|  |  | k1 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 0 | 0.5 | 1 | 5 | 10 | 20 |
| T=1 General surgery | Increase ESS | 0\% | 1\% | 1\% | 3\% | 3\% | 3\% |
|  | Volume dummy surgery | 65\% | 13\% | 13\% | 7\% | 7\% | 7\% |
| Gynecology | Increase ESS | 0\% | 1\% | 1\% | 8\% | 33\% | 33\% |
|  | Volume dummy surgery | 82\% | 18\% | 18\% | 6\% | 0\% | 0\% |
| ENT | Increase ESS | 0\% | 4\% | 4\% | 19\% | 60\% | 60\% |
|  | Volume dummy surgery | 26\% | 7\% | 7\% | 4\% | 0\% | 0\% |
| Eye surgery | Increase ESS | 0\% | 0\% | 0\% | 0\% | 0\% | 0\% |
|  | Volume dummy surgery | 11\% | 4\% | 4\% | 4\% | 4\% | 4\% |
| Orthopedic surgery | Increase ESS | 0\% | 1\% | 1\% | 4\% | 7\% | 22\% |
|  | Volume dummy surgery | 37\% | 5\% | 5\% | 3\% | 3\% | 3\% |
| Plastic surgery | Increase ESS | 0\% | 0\% | 1\% | 1\% | 11\% | 11\% |
|  | Volume dummy surgery | 75\% | 25\% | 13\% | 13\% | 0\% | 0\% |
| Urology | Increase ESS | 0\% | 2\% | 9\% | 9\% | 9\% | 81\% |
|  | Volume dummy surgery | 79\% | 26\% | 15\% | 15\% | 15\% | 5\% |
| $\mathrm{T}=2$ General surgery | Increase ESS | 0\% | 0\% | 1\% | 2\% | 4\% | 5\% |
|  | Volume dummy surgery | 48\% | 11\% | 11\% | 5\% | 5\% | 5\% |
| Gynecology | Increase ESS | 0\% | 1\% | 2\% | 11\% | 19\% | 19\% |
|  | Volume dummy surgery | 50\% | 9\% | 6\% | 3\% | 3\% | 3\% |
| ENT | Increase ESS | 0\% | 4\% | 4\% | 6\% | 6\% | 42\% |
|  | Volume dummy surgery | 15\% | 2\% | 2\% | 2\% | 2\% | 0\% |
| Eye surgery | Increase ESS | 0\% | 2\% | 2\% | 2\% | 2\% | 2\% |
|  | Volume dummy surgery | 8\% | 2\% | 2\% | 2\% | 2\% | 2\% |
| Orthopedic surgery | Increase ESS | 0\% | 0\% | 1\% | 3\% | 3\% | 3\% |
|  | Volume dummy surgery | 21\% | 7\% | 4\% | 1\% | 1\% | 1\% |
| Plastic surgery | Increase ESS | 0\% | 0\% | 1\% | 1\% | 5\% | 5\% |
|  | Volume dummy surgery | 38\% | 13\% | 7\% | 7\% | 0\% | 0\% |
| Urology | Increase ESS | 0\% | 1\% | 2\% | 10\% | 10\% | 10\% |
|  | Volume dummy surgery | 68\% | 21\% | 21\% | 10\% | 10\% | 10\% |

Table 3: Trade off between the increase of ESS and the volume of dummy surgeries when $k_{1}$ is varied.

### 6.3. Discussion

In Beatrix hospital the proposed surgery types were used as input in discussions with surgeons to determine the actual surgery types. They checked for instance whether the surgical cases that were clustered in a single surgery type could be performed by a single surgeon. This enhances easy scheduling of surgeons. Surgery types were adjusted when required, which occurs in approximately $10 \%$ of the surgery types. This was mainly because of surgeon specialization.

During discussion with surgeons and hospital administrators several other issues raised such as decrease in case mix performed by surgeons and the required training of surgeons in certain cases. The organizational structure in Beatrix Hospital is such that the financial pay off for surgeons is based on the volume of their surgical department. Hence, within a single department no competition exists for financial reasons. However, inherent to the MSS approach the number of different surgical cases that a surgeon performs will
decrease. Some surgical departments consider this as positive since the number of repetition increases accordingly. Other departments considered this as negative since surgeons would become less all-round and therefore less flexible to substitute one of their colleagues.

Another issue is whether the data of a previous year is representative for the upcoming year. We believe that in general the variability in length of stay and surgery duration in a upcoming period will be equivalent to a previous period. However, there may be trends in arrival patterns of patients. This may cause the need of adjusting frequencies of surgical cases, which in turn may cause that the solution heuristics would have produced a different set of surgery types. Beatrix hospital did expect trends in arrival patterns (for instance more hip and knee replacements). However, since such high volume surgical cases typically ended up in a surgery type without any other surgical case we have chosen to adjust frequency of surgery types after their construction.

The frequencies of surgery types are based on averages. Seasonal fluctuations and other reasons cause temporarily higher or lower demand. During such period the MSS may face over or under utilization. We study this issue in a forthcoming paper, wherein we show how to deal with this issue by manipulating planning horizon and assignment rules.


Figure 1: Visualization of the results of Orthopedic Surgery in case of an MSS cycle of one week. Volume of dummy surgeries is represented as a percentage of the total Orthopedic case volume.

## 7. Conclusion

In this paper we suggest a method for the constructing of surgery types to allow master surgical scheduling. The method is based on Ward's hierarchical cluster method that uses the error sum of squares as measure for the loss of information. We adjusted this model to account for the volume of dummy surgeries resulting from the clustering of surgery types, as this is important for the functioning of an MSS approach. The method was successfully applied to the case of Beatrix hospital.

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## Chapter 4

## A master surgical scheduling approach for cyclic scheduling in operating room departments

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## Chapter 4

# A master surgical scheduling approach for cyclic scheduling in operating room departments 

Abstract


#### Abstract

This paper addresses the problem of operating room (OR) scheduling at the tactical level of hospital planning and control. Hospitals repetitively construct operating room schedules, which is a timeconsuming, tedious, and complex task. The stochasticity of the durations of surgical procedures complicates the construction of operating room schedules. In addition, unbalanced scheduling of the operating room department often causes demand fluctuation in other departments such as surgical wards and intensive care units. We propose cyclic operating room schedules, so-called master surgical schedules (MSSs) to deal with this problem. In an MSS, frequently performed elective surgical procedure types are planned in a cyclic manner. To deal with the uncertain duration of procedures we use planned slack. The problem of constructing MSSs is modeled as a mathematical program containing probabilistic constraints. Since the resulting mathematical program is computationally intractable we propose a column generation approach that maximizes the operation room utilization and levels the requirements for subsequent hospital beds such as wards and intensive care units in two subsequent phases. We tested the solution approach with data from the Erasmus Medical Center. Computational experiments show that the proposed solution approach works well for both the OR utilization and the leveling of requirements of subsequent hospital beds.


## 1. Introduction

Increasing costs of health care imply pressure on hospitals to make their organization more efficient. Recent studies show that operations research provides powerful techniques in this context (Carter 2002). One of the most expensive resources in a hospital is the operating room (OR) department. Since up to $70 \%$ of all hospital admissions involve a stay in an OR department (OECD 2005), optimal utilization of OR capacity is of paramount importance.

Operating room utilization is typically jeopardized by numerous factors and various players are active in OR planning, such as individual surgeons, OR managers, and anesthesiologists (Weissman 2005). All players have autonomy, and can have conflicting objectives with respect to productivity, quality of care, and quality of labor (Glouberman and Mintzberg 2001). As a result, OR planning is constantly under scrutiny and pressure of potentially competing objectives.

A further complicating factor of the OR planning is the stochastic nature of the process. There are many uncertainties, such as stochastic durations of surgical procedures, no-shows of patients, personnel availability, and emergency surgical procedures. In addition, because surgeons tend to plan their procedures independently from others, this results in peak demands at subsequent hospital resources such as intensive care units
(ICU). As a result, unavailability of for example ICU bed capacity can result in cancelation of surgical procedures (McManus et al. 2003).

In this paper we consider the problem of scheduling elective procedures, which is an operational planning problem that concerns the assignment of elective procedures to ORs over the days of the week. Due to the aforementioned difficulties, the planning process is complex, time consuming, and often under a lot of pressure. However, a lot of elective procedures tend to be identical during consecutive weeks in the year. In a regional hospital it is not uncommon that this is for more than $80 \%$ of the total volume the case (Bakker and Zuurbier 2002). In manufacturing as well as in health care, repetitive production is common practice. In such environments a cyclic planning approach is often used (e.g., Tayur 2000; Schmidt et al. 2001; Millar and Kiragu 1998). This reduces planning efforts considerably, and leads to reduced demand fluctuations within the supply chain, and higher utilization rates.

We propose in this paper a model for a cyclic scheduling approach of elective surgical procedures. We refer to such a cyclic surgical schedule as a master surgical schedule (MSS). An MSS specifies for each "OR-day" (i.e. operating room on a day) of the planning cycle a list of recurring surgical procedure types that must be performed. We demonstrate that our approach is generic: it not only allows to level and control the workload of the involved surgical specialties, but also from succeeding departments such as ICUs and surgical wards. It optimizes OR utilization without increasing overtime and cancelations. Furthermore, our approach accounts for the stochastic nature of the surgical process, such as stochastic durations of surgical procedures.

The approach for generation of MSSs was tested with data from the Erasmus Medical Center in Rotterdam, The Netherlands, which is a large university hospital. Approximately 15,000 patients annually undergo surgery in the OR departments of Erasmus MC. Since 1994, Erasmus MC has collected their surgical data in a database of 180,000 surgical procedures. The hospital actively supported the research project and affirms the applicability of this study.

The remainder of the paper is structured as follows. Section 2 presents an overview of studies related to the problem of construction MSSs. Section 3 presents a base model that represents the problem of constructing MSSs. Section 4 proposes a solution approach to solve the problem. In Sect. 5 we evaluate the solution approach. Section 6 draws conclusions from this research.

## 2. Related literature

There exist a strong interest in OR scheduling problems, resulting in a wide range of papers on this subject. These studies can be separated into short-term operating room scheduling (e.g., Gerhak et al. 1996; Sier et al. 1997; Ozkaraham 2000; Lamiri et al. 2005;

Jebali et al. 2006) and mid-term planning and control (e.g., Guinet and Chaabane 2003; Ogulata and Erol 2003; Kim and Horowitz 2002). Studies about MSS are, however, scarce. Moreover, various definitions of a MSS are used. Blake and Donald (2002) construct MSSs that specify the number and type of operating rooms, the hours that ORs are available, and the specialty that has priority at an operating room. They use an integer programming formulation for the assignment of specialties to operating rooms. The objective function minimizes penalties related to the total under-supply of operating rooms to specialties. The authors implement a straightforward enumerative algorithm, which results in considerable improvements. Beliën and Demeulemeester (2005) use a nonlinear integer programming model to construct MSSs. The model assigns blocks of OR time to specialties in such a way, that the total expected bed shortage on the wards is minimized. After linearization of the model the authors examine and compare several heuristics to solve the resulting mixed integer program. They conclude that a simulated annealing approach yields the best results, but since this heuristic requires much computation time they propose a hybrid algorithm that combines simulated annealing with a quadratic programming model. This approach yields the best results concerning solution quality and computation times. Vissers et al. (2005) propose an MSS approach for a cardiothoracic department. At an aggregate level they form surgical procedure types and level resource requirements such as bed requirements. The objective of their approach is to minimize the deviation of target utilization rates for the OR, the ICU, and the wards. The approach focuses on capacity planning and does not account for the stochastic nature of health care processes.

The aforementioned authors propose various approaches for cyclic OR planning, some of them taking into account succeeding or preceding hospital departments. These approaches are designed for a higher level of aggregation than what we focus on. None actually constructs OR schedules in which actual surgical procedures or procedure types and their stochasticity are incorporated.

## 3. Problem description

The aim of this paper is to develop methods to generate MSSs, i.e., OR schedules that are cyclically executed in a given planning period. The cyclic nature of an MSS requires that not surgical procedures of concrete patients but surgical procedures of a certain type are scheduled. The concrete assignment of patients to the planned procedure types has to be done in a later stage. To make such an approach applicable, the types of surgical procedures must represent surgical procedures, which are medically homogeneous in the sense that they share the same diagnosis and are performed by the same surgical department. In most hospitals there are three categories of types of procedures:

1. Category A: elective procedures that occur quite frequent,
2. Category B: elective procedures that occur rather seldom,
3. Category C: emergency procedures.

Following the above discussion, an MSS can concern only Category A procedures. More precisely, we define Category A procedures as elective procedure types, which have a frequency such that they occur at least once during the cycle time of the MSS. The chosen cycle length thus determines the number of surgical procedure types incorporated in an MSS. Category B procedures consist of all other elective procedures and cannot be planned in an MSS, whereas Category C procedures cannot be planned due to their nature. However, in the construction of an MSS, capacity for the procedures of types B and C will be reserved.

An MSS is part of a cyclic OR planning strategy, which has three stages. First, clinicians and managers determine the MSS cycle length. Correspondingly, they determine how the OR capacity is divided over the three categories. Second, before each cycle, clinicians assign actual Category A patients to the procedure type "slots" in the MSS, and Category B procedures to their reserved capacity. Third, during execution of the elective schedule, Category C (emergency) procedures are scheduled. Widely used approaches are to assign these to reserved capacity (Goldratt 1997), or to capacity obtained by canceling elective procedures (Jebali et al. 2006).

In this paper we propose a model for the construction of MSSs for Category A procedures. Scheduling Category B and C procedures is beyond the scope of this paper. An MSS can be used repetitively by a hospital until the size and the content of the three categories change. Then, the MSS must be reoptimized.

The goal of our MSS is to generate a cyclic schedule, in which all Category A procedures are scheduled according to their expected frequency, in such a way that the workload of subsequent departments like wards and IC is leveled as much as possible. This leveling results in reduction of peak demands on hospital bed departments caused by elective surgical procedures and, as such positively influences resource shortages and minimizes the number of cancelation of surgical procedures McManus et al. 2003. The number of available ORs restricts constructing the MSS as well as the available operating time and the capacity of succeeding departments (i.e., number of available beds). Personnel restrictions are not taken into account. We assume that sufficient flexibility remains for personnel scheduling at the operational level when the scheduling of Category B procedures is done. To avoid the probability of overtime, planned slack is included in the construction of MSSs. The amount of slack depends on the accepted probability that overtime occurs, which is determined by the management, and the variance of procedure durations. We use the portfolio effect to minimize the total amount of required slack (Hans et al. 2006). The portfolio effect is the tendency for the risk of a well-diversified range of stochastic variables to fall below the risk of most and sometimes, all of its individual com-
ponents. This principle can be applied with respect to the stochastic surgery durations. Exploiting the portfolio effect can thus reduce the required amount of slack.

### 3.1. Formal problem description

The surgical procedures to be incorporated into an MSS (Category A procedures) are categorized into $I$ different types of medical and logistical similar procedures. From type $i$, $i=1, \ldots, I$ we have $s_{i}$ procedures to be added in the MSS. The duration of a surgical procedure of type $i$ is a stochastic variable $\xi_{i}$, and based on Strum et al. (2000). We assume that $\xi_{i}$ has a lognormal distribution. Let $B$ be the number of different hospital bed types. The various hospital bed types differ in importance and to indicate the relative importance of hospital bed type $b$ we introduce priority factor $c_{b}$. The duration of hospital bed requirements of type $b$ for a procedure of type $i$ is denoted by $l_{i b} \in \mathbb{N}, i=1, \ldots, I ; b=$ $1, \ldots, B$. We assume that only one patient per day can use a bed.

The MSS has a fixed duration, the cycle length $T$. This cycle length is measured in days and typically is a multiple of 7 days. The given surgical procedures have to be carried out in $J$ identical ORs, where OR $j$ on day $t$ has a capacity of $o_{j t}, j=1, \ldots, J ; t=1, \ldots, T$. For creating an MSS, procedures have to be assigned to the ORs. The total sum of the duration of procedures assigned on a single OR on a specific day may not exceed the available capacity with probability $\alpha$, i.e., with probability $\alpha$ that no overtime occurs. We refer to OR $j$ on day $t$ as OR-day $(j, t)$.

The combined objective of the problem is to construct MSSs such that both the required OR capacity is minimized and the hospital bed requirements are leveled over the cycle.

### 3.2. Base model

In this subsection we give a base model of the MSS problem. The aim of the model is to create a precise description of the objectives and the constraints.

To distinguish between minimization of OR capacity and hospital bed requirement leveling we define a weighted objective function, in which $\theta_{l}$ is the weight of minimization of the required OR capacity and $\theta_{2}$ is the weight of the hospital bed leveling. The weights may for example be related to the costs of the reduction of required OR capacity relative to the costs of peak demand on hospital beds.

We introduce an integer decision variable $V_{i j t}$ to indicate the number of surgical procedures of type $i$ that is assigned to OR-day $(j, t)$, and an auxiliary binary variable $W_{j t}$ to indicate whether an OR $j$ is used on day $t$. An OR is considered to be used on day $t$ if at least one surgical procedure is assigned to this OR-day. The total amount of OR capacity that is made available on day $t$ is the sum of the available capacity of all used ORs. This is
given by

$$
\sum_{t=1}^{T} \sum_{j=1}^{J} o_{j t} \cdot W_{j t}
$$

To calculate the number of beds that is required from hospital bed type $b$, we introduce parameters $\psi_{t t i b}$ that denotes the requirements for hospital bed type $b$ on day $\tau$ for a surgical procedure of type $i$, if this procedure is scheduled on day $t$. More specific, parameter $\psi_{t r i b}$ is $\left\lceil\frac{l_{i b}}{T}\right\rceil$ if $\min \left\{(t-1) \bmod T,\left(t+l_{i b}-2\right) \bmod T\right\} \leq(\tau-1) \leq \max \{(t-$ $1 \bmod T, t+l i b-2 \bmod T$ and $l i b T$ otherwise. To illustrate this expression, suppose an MSS has cycle length $T=7$ days. On day $t=5$, a procedure of type $i$ is scheduled that subsequently requires an IC bed for 8 days $\left(l_{i b}=8\right)$. This results in the requirement of two ICU beds on day $\tau=5$ of the cycle and one IC bed on all other days. On day 5 the requirement is two beds, because the patient of the previous cycle is still occupying an ICU bed.

To level the hospital bed requirements, we minimize the maximum demand for hospital beds during an MSS cycle. This min-max type of resource leveling objective is generally used for problems where resource usage is very expensive (for this and other types, see: Brucker et al. 1999; Neumann and Zimmermann 2000). The presented approach is not specific for beds but can be used similarly for other types of hospital resources.

The maximum demand for hospital bed type $b$ in a cycle is: $\max _{\tau \epsilon T} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \psi_{t \tau i b} \cdot V_{i j t}$. To ensure that the objective function is not influenced by the total requirement of different hospital bed types, but only by their relative importance, we normalize the maximum demand for any hospital bed. The normalization factor is the total demand for a hospital bed type $b$ during one cycle: $\left(\sum_{i=1}^{I} l_{i b} \cdot s_{i}\right) T$. This yields the normative sum of the maximum demand of all hospital bed types:

$$
\sum_{b=1}^{B}\left[\frac{c_{b}}{\left[\sum_{i=1}^{I} l_{i b} \cdot s_{i}\right] T}\right] \cdot \max _{\tau \in T} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \psi_{t \tau i b} \cdot V_{i j t}
$$

The overall objective function consisting of the weighted sum of needed OR capacity and the peak demands of hospital beds is given by formula (1) in the base model presented below.

To ensure that an operating room is considered to be used if at least one procedure is assigned to that operating room, constraints (2) are introduced. Constraints (3) ensure that all surgical procedures of all types are assigned. To model the bound on the probability that overtime occurs, we introduce a function $f_{j t}(V)$. It denotes the probability distribution of the total duration of all procedures that are scheduled on OR-day $(j, t)$ by $V$, where $V$ is the vector of all variables $V_{i j t}$ (a possible way to deal with this function, is given in the following section). Using the function $f_{j t}(V)$, the restriction that the total duration of
procedures on an OR-day may not exceed the available capacity with probability $\alpha$, can be expressed by the probabilistic constraints (5). We refer to Charnes et al. (1964) for detailed information on probabilistic constraints. Summarizing, the base model becomes:

$$
\begin{equation*}
\min \theta_{1} \cdot \sum_{t=1}^{T} \sum_{j=1}^{J} o_{j t} \cdot W_{j t}+\theta_{2} \cdot \sum_{b=1}^{B}\left[\frac{c_{b}}{\left[\sum_{i=1}^{I} l_{i b} \cdot s_{i}\right] T}\right] \cdot \max _{\tau \in T} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \psi_{t \tau i b} \cdot V_{i j t} \tag{1}
\end{equation*}
$$

subject to

$$
\begin{align*}
V_{i j t} \leq s_{i} \cdot W_{j t}, & i=1, \ldots, I, j=1, \ldots, J, t=1, \ldots, T  \tag{2}\\
\sum_{t=1}^{T} \sum_{j=1}^{J} V_{i j t}=s_{i}, & i=1, \ldots, I  \tag{3}\\
\operatorname{Pr}\left[f_{j t}(V) \leq o_{j t}\right] \geq \alpha, & i=1, \ldots, I, j=1, \ldots, J  \tag{4}\\
V_{i j t} \in \mathbb{N}, & i=1, \ldots, I, j=1, \ldots, J, t=1, \ldots, T \\
W_{j t} \in\{0,1\}, & i=1, \ldots, I, \quad t=1, \ldots, T
\end{align*}
$$

The min-max objective can be reformulated (see Williams 1999, p. 23) such that the base model is an integer linear program (ILP) with additional probabilistic constraints. The size of instances from practice gets extremely large (the Erasmus MC instances approximately have $1.9 \times 10^{5}$ decision variables), such that even without the probabilistic constraints this is far too large to solve the model to optimality within reasonable computation time. The MSS problem itself is NP-hard even if the probabilistic effects are neglected. The first part of the objective function together with the packing constraints contains e.g. the bin-packing problem and the second part of the objective function contains e.g. the three-partitioning problem. Based on this, we concentrate on a heuristic approach to solve the MSS problem.

## 4. Solution approach

The main decision in the MSS problem is to fill OR-days $(j, t)$ according to the imposed restrictions. Since in practice the given capacities $o_{j t}$ are often the same for different ORs and for different days, we introduce the concept of so-called operating room day schedule (ORDS). An ORDS for capacity $o$ is a set of surgical procedures of various types, which is feasible with respect to the OR-capacity constraint (5) with $o_{j t}=o$. As a consequence, an ORDS for capacity o can be assigned to all OR-days ( $\mathrm{j}, \mathrm{t}$ ) with ojt $=o$. MSS comprises of assigning one ORDS to each OR-day $(j, t)$ in the cycle, such that the objective function (1) is minimized.

We propose a two-phase decomposition approach. In Phase 1 hospital bed requirement leveling is ignored, and a set of ORDSs that covers all procedures is selected. These ORDSs have capacities fitting to the capacities of the OR- days, and minimize the required OR capacity. We discretize the probabilistic OR capacity constraints, and
formulate an ILP that we solve with an implicit column generation approach. In Phase 2 we assign ORDSs to concrete OR- days in such a way, that the hospital bed capacity demand is leveled. For this purpose, the problem is formulated as mixed integer linear program (MILP).

### 4.1. Phase 1

The problem in Phase 1 consists of selecting a set of ORDSs that covers all surgical procedures and all OR-day capacities and minimizes the required OR capacity. In Sect. 4.1.1 we formalize the problem as an ILP problem where the variables correspond to ORDSs of given capacities. Afterwards, in Sect. 4.1 .2 we propose a column generation approach to generate possible ORDSs. In this part we discretize the probabilistic constraints on the ORDSs.

## Phase 1 model

The available capacity of ORs in the MSS cycle may differ from day to day. Let $R$ be the number of different OR capacity sizes (sorted in non-decreasing order). The actual capacity of an OR of capacity size type $r$ is given by $d_{r}, r=1, \ldots, R$. Let $U$ be the set of possible ORDSs, and let $U_{r}$ be the subset of U that contains all the ORDSs that belong to the $r^{\text {th }}$ capacity size. In this context an ORDS $u$ belongs to $U_{r}$ if the $r^{\text {th }}$ capacity size is the smallest available capacity size where the ORDS fits in. Hence, $U=\bigcup_{r=1}^{R} U_{r}$. Let $m_{r}$ be the number of OR-days within one cycle length that have the $r^{\text {th }}$ capacity size and let $\phi_{r}$ be the set of corresponding tuples $(j, t)$. For a given ORDS $u \in U$ we denote the number of surgical procedures of type $i$ that are scheduled in $u$ by $a_{i u} \in \mathbb{N}$.

To formulate the Phase 1 model, we introduce integer decision variables $X_{u}$ ( $u \in U$ ) that represent the number of times that ORDS $u$ is selected. The objective function (5) corresponds to the first part of the objective function (1) of the base model: minimization of the required OR capacity. Constraints (6) impose that all procedures are selected. The number of ORDSs generated for every OR capacity size that we can select is restricted by the number of available OR-days $m_{r}$ of capacity type $r$. This restriction is imposed by constraints (7). Summarizing, in Phase 1 we must solve the following ILP:
subject to

$$
\begin{array}{cc}
\min \sum_{r=1}^{R} \sum_{u \in U_{r}} d_{r} \cdot X_{u} & \\
\sum_{r=1}^{R} \sum_{u \in U_{r}} a_{i u} \cdot X_{u} \geq s_{i}, & i=1, \ldots, I \\
\sum_{u \in U_{r}} X_{u} \leq m_{r}, & r=1, \ldots, R  \tag{7}\\
X_{u} \in \mathbb{N}, & u \in U .
\end{array}
$$

This model has two main drawbacks. The set of possible ORDSs $U$ grows exponentially with the number of procedure types, and due to the probabilistic constraints, the identification of all possible elements of U is difficult. To overcome this, a column generation approach for this problem is presented where furthermore the check on containment of an ORDS in a set Ur is discretized.

## Column generation

Column generation is an often-used approach to solve complex optimization problems with a large number of variables (e.g. cutting stock, capacity planning, and crew scheduling, e.g., Barnhart et al. 1998; Pinedo 2005). The outline of our approach is as follows. We use column generation to solve the LP relaxation of the Phase 1 model, and round this solution to obtain a feasible solution. In the column generation procedure we iteratively generate subsets of $U$ (i.e., subsets of ORDSs) and solve the Phase 1 model for these subsets. The Phase 1 model restricted to such a subset of $U$ is called the restricted master problem. In each iteration, solving the restricted LP-relaxation (i.e. the LPrelaxation of the restricted master problem) yields shadow prices. These are used as input for the sub-problem (the pricing problem), which revolves around generating ORDSs that are not included in the restricted master problem, but that may improve its solution. The reduced costs of the corresponding variables $X_{u}$ are negative. These ORDSs are added to the restricted master problem, and the LP-relaxation is re-optimized. This procedure stops if no ORDSs exist that may improve the restricted LP-relaxation solution. The restricted LP-relaxation solution is then optimal to the LP-relaxation. We then apply a rounding procedure to obtain a feasible Phase 1 solution.

Initialization We use an initialization heuristic to generate subsets of $U_{r}$ for all OR capacity sizes $r=1, \ldots, R$. More precisely, for each $r=1, \ldots, R$ we generate subsets $\bar{U}_{r} \subset U$ of ORDSs that cover all surgical procedures. This initial set of ORDSs serves as a starting point for the column generation procedure.

Let the variable $Z_{i}^{r} \in \mathbb{N},(i=1, \ldots, I)$ denote the number of procedures of type $i$ that is scheduled in an ORDS for OR capacity size $r$. Any vector $Z^{r}=\left(Z_{1}^{r}, \ldots, Z_{I}^{r}\right)$ must satisfy the probabilistic bin-packing constraint (8) to be a feasible ORDS for capacity size $r$, where $f\left(Z^{\prime}\right)$ denotes the distribution function that represents the stochastic sum of the duration of all surgical procedures in the ORDS.

$$
\begin{equation*}
\operatorname{Pr}\left[f\left(Z^{r}\right) \leq d_{r}\right] \geq \alpha \tag{8}
\end{equation*}
$$

The probabilistic constraints (8) impose difficulties on the generation of ORDSs. We discretize constraints (8) using prediction bounds. A prediction bound $n_{i}^{\alpha}$ denotes that the duration $\xi_{i}$ of procedure type $i$ is smaller than or equal to $n_{i}^{\alpha}$ with a probability $\alpha$. These prediction bounds are used to replace the stochastic variables $\xi_{i}$, and can be calculated using the primitive of the distribution function of $\xi_{i}$. The total required OR capacity for an ORDS given by the vector $Z^{r}$ is given by $\sum_{i=1}^{I} n_{i}^{\alpha} \cdot Z_{i}^{r}$. The difference between the value of
a prediction bound and the average surgical procedure duration is used to compute the planned slack.

As discussed by Hans et al. (2006) the total amount of planned slack for a multiple of surgical procedures is reduced by the portfolio effect. This portfolio effect may be approximated by a function $g$, which only depends on the number of procedures that are scheduled in the operating room and on the average standard deviation of all types of surgical procedures. The reduction of required planned slack $g\left(\sum_{i=1}^{l} Z_{i}^{r}\right)$, as a result of the portfolio effect, is subtracted from the sum of the prediction bounds. This results in the following OR capacity constraints:

$$
\begin{equation*}
\left(\sum_{i=1}^{I} n_{i}^{\alpha} \cdot Z_{i}^{r}\right)-g\left(\sum_{i=1}^{I} Z_{i}^{r}\right) \leq d_{r} \tag{9}
\end{equation*}
$$

All vectors $\left(Z_{1}^{r}, \ldots, Z_{I}^{r}\right)$ that satisfy constraints (9) are possible elements of $U_{r}$. Since the generation of ORDS is basically a bin-packing problem, we may apply binpacking heuristics such as First Fit Decreasing (FFD), Best Fit Decreasing (BFD) and Minimum Bin Slack (MBS) (Gupta and Ho 1999) or a heuristic such as Randomized List Scheduling Heuristic (van den Akker et al. 1999) to generated initial set of ORDSs. Since in a study of off-line bin-packing algorithms by Dell’Olmo and Speranza (1999) Longest Processing Time (LPT) performs well, we use this heuristic for the generation of an initial set of ORDSs for an OR capacity size $r$. LPT first sorts all procedures of all types in decreasing order of their prediction bound $n_{i}^{\alpha}$ and then it creates an ORDS in which it plans the longest procedure that fit, i.e., that satisfy constraints (9). If the heuristic reaches the end of the ordered list it closes the ORDS. This is repeated until no surgical procedures remain in the ordered list. The heuristic is executed for all OR capacity sizes.

Pricing problem An optimal solution of the LP relaxation of the restricted problem is optimal for the LP relaxation of the complete master problem if the corresponding dual solution is feasible for the dual problem of the LP relaxation of the master problem. The pricing problem is thus to determine whether there exist ORDSs that are not in the restricted LP relaxation that violate the dual constraints from the LP relaxation of the master problem. Such ORDSs are added to the restricted LP relaxation and a next iteration starts. If such ORDSs do not exist, column generation terminates, and the current restricted LP relaxation solution is optimal to the LP relaxation of the master problem.

The dual constraints of the LP relaxation of the Phase 1 model are:

$$
\begin{array}{rc}
\pi_{r}+\sum_{i=1}^{I} \lambda_{i} \cdot a_{i u} \leq d_{r}, & r=1, \ldots, R \\
\pi_{r} \leq 0, & r=1, \ldots, R  \tag{10}\\
\lambda_{i} \geq 0, & i=1, \ldots, I
\end{array}
$$

where $\lambda_{i}$ are the dual variables corresponding to constraints (6), and $\pi_{r}$ the dual variables corresponding to constraints (7) of the Phase 1 LP.

As input for the pricing problem we obtain two vectors $(\bar{\pi}, \bar{\lambda})$ of shadow prices from the restricted LP relaxation. The pricing algorithm now examines whether for this solution $(\bar{\pi}, \bar{\lambda})$ an ORDS $u \in U_{r}$, represented by $a_{I u}, \ldots, a_{I u}$, exists that violates the dual constraint (10), i.e. values $a_{I u}, \ldots, a_{I u}$, with:

$$
\begin{equation*}
d_{r}-\bar{\pi}_{r}-\sum_{i=1}^{I} \bar{\lambda} \cdot a_{i u}<0 \tag{11}
\end{equation*}
$$

The left-hand side of constraints (11) are the reduced costs for variable $X_{u}\left(u \in U_{r}\right)$. We evaluate each OR capacity size $r$ separately to determine whether an ORDS exists, formed by a vector $\left(Z_{i}^{r}, \ldots, Z_{I}^{r}\right)$, that violates the dual constraints (10). In the $r^{\text {th }}$ problem we thus need to maximize

$$
\sum_{i=1}^{I} \bar{\lambda}_{l} \cdot Z_{i}^{r}
$$

over all vectors $\left(Z_{i}^{r}, \ldots, Z_{I}^{r}\right)$ representing a new ORDS, i.e. satisfying constraint (9).
To solve the pricing problem as an ILP we write the term: $g\left(\sum_{i=1}^{l} Z_{i}^{r}\right)$ as a telescopic sum. For this purpose, we introduce additional notation. The binary variable $A_{e}$ indicates whether there are at least $e$ procedures in an ORDS ( $e \leq E$, where $E$ is the maximum number of procedures that can be performed during 1 day in one operating room). The function $g(e):=g_{1}+\cdots+g_{e}$ provides the correction for the portfolio effect for $e$ surgical procedures. Using this function and the binary variables $A_{e}$, the $r^{\text {th }}$ pricing problem ILP becomes:

$$
\max \sum_{i=1}^{I} \bar{\lambda}_{i} \cdot Z_{i}^{r}
$$

subject to

$$
\begin{array}{rr}
\left(\sum_{i=1}^{I} n_{i}^{\alpha} \cdot Z_{i}^{r}\right)-\sum_{e=1}^{I} g(e) \cdot A_{e} \leq d_{r}, & r=1, \ldots R \\
\sum_{i=1}^{I} Z_{i}^{r}=\sum_{e=1}^{E} A_{e}, & e=1, \ldots, E \\
A_{e} \geq A_{e+1}, & e=1, \ldots, E
\end{array}
$$

$$
\begin{aligned}
& A_{e} \in\{0,1\}, \\
& Z_{i}^{r} \in \mathbb{N}, i=1, \ldots, E \\
&
\end{aligned}
$$

After this problem is solved for all capacity sizes r , the resulting ORDSs with negative reduced costs are added to the restricted LP relaxation of the Phase 1 model. This model is reoptimized to obtain new shadow prices. Column generation stops if no such ORDSs are found any more. If in practice this process takes very long and generates a large number of extra columns, one might incorporate some of the stopping criteria like the amount of improvement in the LP resulting from the newly generated columns. This may have some effect on the quality of the LP-solution, but since afterwards still an integer solution has to be constructed, the effect on the solution after Phase 2 might be only marginal. In our test instances, we always were able to solve the LP-relaxation to optimality.

Rounding heuristic The solution to the restricted LP relaxation does not directly lead to a starting point for the second phase, since ORDSs may have been selected fractionally. To obtain an integer solution we use a rounding heuristic that rounds down the fractional solution. This results in an integer solution with a small number of surgical procedures that are not assigned to selected ORDSs. These procedures are assigned to newly created ORDSs using an LPT heuristic. There may also be some redundant surgical procedures due to the " $\geq$ " sign in constraints (6). We remove these redundant procedures randomly. In general, this approach does not guarantee to result in a feasible solution. However, for the tested instances a quite large fraction of procedures was planned before rounding, only a fraction had to be planned by the LPT heuristic. We never got stuck with infeasible solutions at this stage. If infeasibility might get an issue, the simple rounding heuristic leave room for algorithmic improvements and may be replaced by more elaborate approaches. Summarizing, the output of Phase 1 consists of a set of ORDSs that cover the set of all surgical procedures to be assigned within the MSS.

### 4.2. Phase 2

In Phase 2 the actual MSS cycle is constructed. We propose an ILP in which the set of ORDSs is assigned to OR-days such that the hospital bed requirements are leveled over the days.

## Phase 2 model

Given is a set $\bar{U}$ of ORDSs to be assigned to the OR-days of the MSS. Let $\bar{U}_{r} \subset \bar{U}$ denote the ORDSs which are of capacity size $r$. To model the assignment of an ORDS $u$ to an OR-day $(j, t)$ we introduce binary decision variables $Y_{u j t}$ for all $u \in \bar{U}_{r}$ and $(j, t) \in \varphi_{r}$. We ensure that the OR capacity sizes match and that at most one ORDS is assigned to an OR on a day. The objective function takes into account the requirements for all hospital
beds for all days within one MSS cycle, thus also requirements of surgical procedures that have taken place in previous cycles. Corrected by a normalized priority factor (see Sect. 3.2), we minimize the maximum requirements for hospital beds. The objective function is the second term of the objective function (1) of the base model. This objective function is a minimax objective and can be rewritten to Eq. (12) and constraints (13) in which $H B_{b}$ is the maximum requirement of hospital bed type $b$ on a given day in the cycle.

All selected ORDSs from Phase 1 must be assigned to an operating room and a day. This is ensured by constraints (14). No more than one ORDS can be assigned to an operating room on a day, which is imposed by constraints (15). Summarizing, the model of Phase 2 is the following ILP:

$$
\begin{equation*}
\min \sum_{b=1}^{B}\left[\frac{c_{b}}{\left[\sum_{i=1}^{I} l_{i b} \cdot s_{i}\right] T}\right] \cdot H B_{b} \tag{12}
\end{equation*}
$$

subject to

$$
\begin{align*}
\sum_{r=1}^{R} \sum_{u \in \bar{U}_{r}} \sum_{(j, t) \in \varphi_{r}} \sum_{i=1}^{I} \sum_{t=1}^{T} \psi_{t \tau i b} \cdot a_{i u} \cdot Y_{u j t} \leq H B_{b}, & \tau=1, \ldots, T, \quad b=1, \ldots, B  \tag{13}\\
\sum_{(j, t) \in \varphi_{r}} Y_{u j t}=X_{u}, & r=1, \ldots, R, u \in \bar{U}_{r}  \tag{14}\\
\sum_{u \in \bar{U}_{r}} Y_{u j t} \leq 1, & r=1, \ldots, R, \quad(j, t) \in \varphi  \tag{15}\\
Y_{u j t} \in\{0,1\}, & u \in \bar{U}_{r},(j, t) \in \varphi_{r} \\
H B_{b} \geq 0, & b=1, \ldots, B
\end{align*}
$$

## Solving the Phase 2 model

We solve the Phase 2 model using the commercial solver ILOG CPLEX 9.0. We use lower bound on the values HBb to determine the quality of an intermediate solution and to speed up the computation. These lower bounds are calculated by rounding up the sum of the total requirements of hospital beds during one cycle divided by the cycle length:

$$
\left\lceil\frac{\sum_{i=1}^{I} l_{i b} \cdot s_{i}}{T}\right\rceil
$$

This represents a theoretical minimum of the maximum requirements for hospital bed type b on 1 day in a cycle. The lower bounds are multiplied by the normative sum used in the objective (1) of the base model:

$$
\begin{equation*}
\sum_{b=1}^{B}\left[\frac{c_{b}}{\left[\sum_{i=1}^{I} l_{i b} \cdot s_{i}\right] T}\right] \cdot\left\lceil\frac{\sum_{i=1}^{I} l_{i b} \cdot s_{i}}{T}\right\rceil \tag{16}
\end{equation*}
$$

This overall lower bound (16) is given as an initial lower bound to CPLEX to speed up the branch-and-bound process.

## 5. Computational experiments

We implemented the two-phase approach in the AIMMS mathematical modeling-language 3.5 (Bisschop 1999), which interfaces with the ILOG CPLEX 9.0 LP/ILP solver. We test our approach with realistic data instances from the Erasmus MC based on the available database of surgical procedures that has been collected from 1994 until 2004. This data consists of the frequency of surgical procedures, procedure durations, and data about the usage of hospital beds after surgical procedures.

### 5.1. Instance generation

Since 1994 Erasmus MC has been collecting data on the frequency of surgical procedures, the duration of procedures, and standard deviation of the duration of procedures. In cooperation with surgeons we defined procedure types by grouping medically homogeneous procedures, which results in the Erasmus MC instance. The data consist for each surgical procedure type $i$ of the frequency of a surgical procedure type during one cycle $s_{i}$, the prediction bound $n_{i}^{\alpha}$, and the length of a request of a hospital bed $l_{i b}$. We vary the parameter values of the cycle length $T$, the number of operating rooms $J$, and the number of hospital bed types $B$ (see Table 1), which results in 36 instances types. For each parameter combination 9 additional instances are generated, this yields a total of 360 instances. The additional instances are generated by randomly drawing data from the intervals in Table 2 and rounding them to the nearest integers (the values with a tilde in the table represent the values of the parameters resulting from the Erasmus MC instance).

The cycle length influences the number of procedure types and the number of surgical procedures that can be incorporated into the MSS (Category A procedures). Table 3 shows the dependency between the cycle length and the number of surgical procedure types in Category A together with their numbers and total duration.

| Cycle length in days | $T \in\{7,14,28\}$ |
| :--- | :--- |
| Number of operating rooms | $J \in\{5,10,15,20\}$ |
| Number of hospital bed types | $B \in\{1,2,3\}$ |

Table 1: Parameter values for the instances
$s_{i} \in\left[0.9 \cdot \tilde{s}_{i}, 1.1 \cdot \tilde{s}_{i}\right]$
$n_{i}^{\alpha} \in\left[0.9 \cdot n_{i}^{\alpha}, 1.1 \cdot n_{i}^{\alpha}\right]$
$l_{i b} \in\left[0.9 \cdot l_{i b}, 1.1 \cdot l_{i b}\right]$

Table 2: Intervals for creating instances

| Cycle length <br> in days | Number of <br> procedure types | Total number <br> of procedures | Total duration of all <br> procedures (in hours) |
| :--- | :--- | :--- | :--- |
| 7 | 42 | 56 | 126 |
| 14 | 109 | 177 | 398 |
| 28 | 203 | 423 | 952 |

Table 3: The relation between the cycle length and procedures in Category A

| e | 1 | 2 | 3 | 4 | 5 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| $\mathrm{~g}(\mathrm{e})$ | $0.00 \cdot \sigma$ | $0.10 \cdot \sigma$ | $0.22 \cdot \sigma$ | $0.36 \cdot \sigma$ | $0.48 \cdot \sigma$ |

Table 4: Parameter values for function g, to model he portfolio effect
We assume that all ORs are available during weekdays and are closed for elective procedures in weekends. For the computational experiments in this paper we use one OR capacity size $(R=1)$ of $450 \mathrm{~min}\left(d_{r}:=450\right)$. Furthermore, we assume that procedures are finished before their prediction bound in $69 \%$ of the cases, i.e., $\alpha:=69 \%$. This value is taken from the current practice of Erasmus MC. The priority factors of hospital beds are given by: $c(1):=5 \quad c(2):=2 \quad c(3):=1$.

The function $g$, which we use to model the portfolio effect, depends on the number of procedures that is scheduled in an ORDS and the average standard deviation $\bar{\sigma}$ of all surgical procedures. We approximate the portfolio effect using the function $g(e)$ that takes the values indicated in Table 4. The value for the average surgical procedure standard deviation $\bar{\sigma}$ is 36 , based on the database of the Erasmus MC.

### 5.2. Test results

In the tests we focus on three different aspects. Firstly, we study the dependencies of the computation times of both phases on the used parameter combinations. Secondly, we investigate the obtained results of the minimization of the required OR capacity. And finally, we address the hospital bed leveling. For this last issue, we have truncated computations that exceed 600 s . and have used the best incumbent solutions as output. These incumbent solutions are, therefore, generally not optimal for the Phase 2 model.

## Computation times

Table 5 presents the computation times in Phase 1 for all parameter combinations. The computation times in Phase 1 include the initialization and rounding heuristic.

The computation time increases with $T$, whereas $B$ and $J$ hardly influence the computation time. Similar results are obtained when computation times of the initialization

| $\mathrm{T} \rightarrow 7$ |  |  |  | 14 |  |  | 28 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{J} \downarrow \mathrm{B} \rightarrow$ | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 5 | 15.10 | 17.08 | 13.76 | 43.91 | 47.00 | 45.90 | 80.96 | 78.78 | 74.56 |
| 10 | 15.29 | 16.59 | 13.36 | 47.12 | 44.28 | 45.62 | 80.24 | 83.90 | 87.01 |
| 15 | 16.29 | 16.12 | 13.17 | 47.24 | 44.70 | 44.03 | 80.20 | 75.96 | 95.17 |
| 20 | 15.01 | 16.73 | 14.35 | 48.01 | 45.94 | 42.39 | 81.07 | 75.00 | 89.70 |

Table 5: Computation times of Phase 1 in relation with $T, B$ and $J$

| $\mathrm{T} \rightarrow$ | 7 |  |  | 14 |  |  | 28 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{J} \downarrow \mathrm{B} \rightarrow$ | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 5 | 0.30 | 0.49 | 0.56 | 1.55 | 2.79 | 3.69 | 6.16 | 8.94 | 13.32 |
| 10 | 0.63 | 0.93 | 1.11 | 3.78 | 5.86 | 72.04 | 15.02 | 30.54 | 325.08 |
| 15 | 0.96 | 1.37 | 121.60 | 5.39 | 8.69 | 72.92 | 18.87 | 43.09 | 517.08 |
| 20 | 1.21 | 1.81 | 122.27 | 7.45 | 11.26 | 87.79 | 24.54 | 47.25 | 478.67 |

Table 6: Computation times of Phase 2 in relation with $T, B$ and $J$
heuristic are considered solely. Here the computation times vary from 0 to 6 s . We conclude that the initialization heuristic only needs a small fraction of time that is required by the complete Phase 1 computation. Table 6 presents the computation time in Phase 2 for all parameter combinations.

Table 6 shows that all three parameters have considerable impact on the computation time and in all cases the computations time increases with increasing parameter value. Table 7 shows the number of times that the calculation is truncated after 600 s . for all parameter combinations. The '-' sign denotes that these test instances are infeasible due to the lack of operating rooms.

The extreme growth of the computation time for some of the test instances in Table 6 results mainly from hard instances, where the calculation is truncated (see Table 7). Computation times are not high and therefore allow use of the proposed approach in practice.

| $\mathrm{T} \rightarrow 7$ |  |  |  | 14 |  |  | 28 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{J} \downarrow \mathrm{B} \rightarrow$ | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 5 | 0 | 0 | 0 | - | - | - | - | - | - |
| 10 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 3 |
| 15 | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 7 |
| 20 | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 5 |

Table 7: The number of times that computation is truncated

| T $\downarrow$ | Initialization heuristic and column generation |  | Initialization heuristic only |
| :---: | :---: | :---: | :---: |
|  | Required number of operating rooms during 1 week | Rounding gap(\%) | Required number of operating rooms during 1 week |
| 7 | 16.50 | 1.25 | 16.50 |
| 14 | 27.80 | 0.9 | 27.80 |
| 28 | 34.18 | 0.6 | 34.33 |

Table 8: Test results of Phase 1

## OR utilization

Table 8 shows the average number of required ORs per week in relation to the cycle length $T$. The number of required ORs increases if the cycle length increases, which may be expected since the total surgical procedure volume increases as well (see Table 3). The rounding gap between the integer solution of Phase 1 and the value after rounding up the optimal fractional solution of the LP relaxation denotes the quality of the rounding heuristic. We conclude that the rounding gap is small and decreases if more ORDSs are required. Thus, we may conclude that the achieved OR utilization after Phase 1 is close to the best possible utilization.

Table 8 gives the results of using only the ORDSs generated by the initialization heuristic. These values are found by solving the restricted LP using the initially generated ORDSs and applying the rounding heuristic. They are equal to the values of the complete column generation approach for the construction of MSSs with the cycle length of 7 and 14 days. For larger instances with the cycle length of 28 days, the complete column generation slightly improves the initialization heuristic. Thus, in most of the cases, the ORDSs generated by the initial heuristic already contain the ORDSs needed for the optimal fractional solution of the LP-relaxation of the Phase 1 model. But since an MSS is typically constructed once a year, the additional computational effort of the column generation approach should be used to try to improve the initial solution.

## Hospital bed leveling

In this section we discuss the hospital bed leveling. The relative difference between the objective value of the Phase 2 model and the lower bound [see expression (16)] indicates the quality of the solutions found. Table 9 presents the relative differences.

The results in Table 9 show that the difference between the found solutions and the lower bound is small. Therefore, Phase 2 almost optimally levels the hospital bed requirements. This is the more surprising, since the ORDSs in Phase 1 have been generated with the only goal to optimize resource utilization not taking into account the subsequent problem of hospital bed leveling.

| $\xrightarrow{\mathrm{J}} \downarrow$ | $\mathrm{T} \rightarrow$ | 7 |  |  | 14 |  |  | 28 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | B $\rightarrow$ | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 5 |  | 0.0\% | 0.0\% | 0.5\% | - | - | - | - | - | - |
| 10 |  | 0.0\% | 0.0\% | 0.5\% | 0.0\% | 0.0\% | 0.2\% | 0.0\% | 0.0\% | 1.3\% |
| 15 |  | 0.0\% | 0.0\% | 0.5\% | 0.0\% | 0.0\% | 0.2\% | 0.0\% | 0.0\% | 2.4\% |
| 20 |  | 0.0\% | 0.0\% | 0.5\% | 0.0\% | 0.0\% | 0.2\% | 0.0\% | 0.0\% | 1.5\% |

Table 9: Average gap between the lower bound and the Phase 2 solution


Table 10: Average gap between the lower bound and the Phase 2 solution for truncated instances

In 22 out of 360 experiments the computation of Phase 2 is truncated. Table 10 presents the relative differences between the found solution and the lower bound for the 22 truncated instances.

Even for these instances the average gap is small; the maximum gap is $10.1 \%$. Based on the presented results we conclude that the constructed MSSs level the hospital bed requirements of the incorporated surgical procedures. This means that the requirements on one day rarely exceed the lower bound.

## 6. Conclusions and further research

The computational experiments show that generation of MSSs is well possible within acceptable time bounds by the proposed two-phase decomposition approach. The proposed solution approach generates MSSs that minimize the required OR capacity for a given set of procedures and level the hospital bed requirements well. The chosen solution approach makes it possible to add restrictions imposed by personnel and to consider other types of hospital resources than beds. This flexibility is required to implement an OR planning strategy that includes an MSS. The approach has been successfully tested on real data from Erasmus MC. The hospital management is pleased with the outcomes, and encourages and initiates further research into implementing the MSS-approach in practice.

In further research we will investigate implementation aspects, and scheduling of Category B and C procedures as such is required to determine the overall benefits of cyclic
scheduling of OR departments. This research should also provide insight into the benefits of a cyclic OR planning approach for hospitals with various patient mixes. Furthermore, we will investigate the leveling of hospital beds when the length of request for beds is assumed to be stochastic.

The repetitive nature of our cyclic surgical planning approach yields that it reduces the overall management effort. In addition, it not only optimizes OR utilization but also levels the output towards wards and ICU. This results in less surgery cancelations, and thus a reduction of the lead-time of the patient's care pathway. Therefore, MSS contributes to an improved integral planning of hospital processes. The intensive cooperation with clinicians and OR managers has lead to a framework for cyclic OR planning and a method for construction of MSSs that can handle constraints imposed by health care processes. This flexibility ensures the applicability of the developed method in OR departments and hospitals.

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## Chapter 5

Fewer intensive care unit refusals and a higher capacity utilization by using a cyclic surgical case schedule

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## Chapter 5

# Fewer intensive care unit refusals and a higher capacity utilization by using a cyclic surgical case schedule 

Abstract


#### Abstract

PURPOSE: Mounting health care costs force hospital managers to maximize utilization of scarce resources and simultaneously improve access to hospital services. This article assesses the benefits of a cyclic case scheduling approach that exploits a master surgical schedule (MSS). An MSS maximizes operating room (OR) capacity and simultaneously levels the outflow of patients toward the intensive care unit (ICU) to reduce surgery cancellation. MATERIALS AND METHDOS: Relevant data for Erasmus MC have been electronically collected since 1994. These data are used to construct an MSS that consisted of a set of surgical case types scheduled for a period or cycle. This cycle was executed repetitively. During such a cycle, surgical cases for each surgical department were scheduled on a specific day and OR. The experiments were performed for the Erasmus University Medical Center and for a virtual hospital. RESULTS: Unused OR capacity can be reduced by up to $6.3 \%$ for a cycle length of 4 weeks, with simultaneous optimal leveling of the ICU workload. CONCLUSIONS: Our findings show that the proposed cyclic OR planning policy may benefit OR utilization and reduce surgical case cancellation and peak demands on the ICU.


## 1. Introduction

Mounting health care costs force hospital managers to maximize utilization of scarce resources and simultaneously improve access to hospital services. Efforts are therefore directed at developing planning methods that may deal with these seemingly conflicting objectives [1].

Typically, Dutch hospitals use a block planning approach for surgical scheduling [2]. In this approach, surgeons of various departments plan their patients in blocks of operating room (OR) time assigned to their specific department. The method of planning largely determines the utilization of the available OR capacity and thus the efficiency of the OR department. Implicitly a substantial part of the surgical schedules is basic and performed in a cyclic manner. In addition, the surgical schedule determines the daily number of patients flowing from the OR to the intensive care unit (ICU) postoperatively and hence influences surgical and nonsurgical patients' access to the ICU. Scheduling surgical cases without taking into account the inherent ICU or ward occupancy will result in peak demands on these hospital resources. Such peak demands may lead to bed shortages and thus to cancellation of surgical cases or refused ICU admissions for other
indications [3]. Moreover, the uncertain duration of operations and ICU stay, as well as the unforeseeable emergency cases, is a complicating factor in surgical scheduling.

Faced with similar challenges regarding availability of services, peak demands, and capacity utilization, industry has developed methods to deal with these problems. One of these methods is to explicit create and use master schedules, which are repetitively used, for subsequent production steps. In such a master schedule, repetitive jobs are scheduled leading to improved utilization of scarce resources and coordination in the supply chain [4,5].

Based on this experience, the aim of this study is to assess, by means of computational experiments, the benefit of a comprehensive cyclic case schedule for a university hospital and a virtual hospital with a different case mix.

## 2. Materials and methods

Erasmus MC's main OR department consists of 16 ORs. Planning data have been electronically collected since 1994. From this extensive database, we obtained data on frequencies and durations of specific surgical cases and on the standard deviation of duration of all surgical cases. We also obtained data on related length of stay in the ICU if applicable. Erasmus MC has a tertiary referral case mix. Its mean utilization rate was 85.5\%.

The Erasmus MC case mix differed from case mixes of community hospitals. Therefore, besides the experiments using Erasmus MC data, experiments are performed using a case mix of a virtual hospital. The procedure for constructing a data set of the virtual hospital was as follows. The surgical cases from the Erasmus MC data set were put in descending order of frequency. We then selected surgical cases from the ordered list until half of the total surgery volume of the Erasmus MC was accounted for. Subsequently, the frequency was doubled to obtain a case mix with the same volume as the case mix of the Erasmus MC. Table 1 depicts the data for Erasmus MC and the virtual hospital.

We used the block planning method that is currently used in the Erasmus MC as starting point for the analysis [2,6]. In the Erasmus MC's block planning method, months in advance blocks are assigned to surgical department that subsequently plan their patients in the available OR time according to strict rules. One of these rules is to plan reserved OR time for emergency patients and the reduction of overtime [7-10]. The amount reserved for the latter depends upon a chosen probability, which is in the Erasmus MC set at $31 \%$.

|  | Erasmus MC | Virtual hospital |
| :--- | :---: | :---: |
| Data |  |  |
| Total annual case volume (h) | 18549 | 18861 |
| Mean case duration (min) | 142 | 104 |
| Standard deviation (min) | 36 | 30 |
| Mean no. of required ICU beds | 6 | 5 |
| per day |  |  |
| Assumptions | 85.5 | 85.5 |
| $\quad$ Mean OR utilization (\%) | 31 | 31 |
| Accepted risk on overtime (\%) |  |  |

Table 1: Descriptive characteristics of the data sets of Erasmus MC and the virtual hospital
The use of a master surgical schedule (MS S) implies the following 3 stages in the case scheduling process. First, the length of a cycle period is determined, and an MSS is constructed for that period. Thereafter, surgical departments will assign actual patients to the surgical case types incorporated in the MSS. Patients who require a surgical case that is not incorporated may be scheduled in one of the OR blocks that are kept free. At this stage, all patients are assigned to a specific day, for which the clinicians can make the appointments with the patient for surgery. Stage 3 finally provides for the admission of emergency cases and possible replanning of elective cases.

The focus of this article is on the first stage, that is, determining the optional cycle period and the construction of an MSS for such a period. The choice for a particular cycle period was of importance because it determined the number of surgical cases that could be incorporated in the schedule. A longer cycle period lead to a larger set of surgical cases that is on average performed at least once. Given the cycle length and, consequently, the number of case types per cycle, the optimal case schedule was constructed using mathematical optimization techniques. Its ultimate aim was 2 -fold: optimizing the use of OR time and minimizing the peak demands of required ICU beds for elective surgical patients [8]. We applied the method of Van Oostrum et al [8], by which first the OR utilization is maximized by reducing the unused OR capacity, and subsequently the ICU bed requirements are leveled. Maximization of OR capacity was accomplished by generating sets of case types that fitted in one OR, such a set is referred to as Operating Room Day Schedule (ORDS). A column-generation approach generated and selected an optimal set of ORDSs [11].


Figure 1: Overview methodology for construction of an MSS.


Figure 2: Operating room utilization for both hospitals and various cycle periods.

Such an approach starts with an initial set of ORDSs that is generated by a longest processing time heuristic [12]. A longest processing time heuristics applied to surgical case scheduling orders at first all case types based on their expected duration. Then, the first case in line is selected and scheduled in an empty ORDS, followed by the next ones in line unless the sum of durations exceeds the available OR time of the ORDS under consideration. Upon this moment, a new ORDS is created, and the heuristic continues adding surgical cases until the capacity limit is exceeded. After all case types are scheduled
this way, an initial set of ORDSs is created, which covers all case types to be scheduled in the MSS.

Subsequently, the unused time (slack) in the ORDSs is calculated, and applying linear programming (LP) techniques, a new ORDS is constructed, which may reduce the total capacity needed. This ORDS is added to the available set of ORDSs. A selection of ORDS is made using LP techniques, which covers all-surgical case types; and again, the slack in the all ORDS is calculated [8]. Using the renewed slack calculation, a new ORDS that may reduce the required OR capacity is constructed and added to the existing set of ORDS. These steps are repeated until no ORDS can be constructed, which possibly benefit the amount of required OR capacity.

Hence, each ORDS consists of case type that causes a certain bed requirement profile. To reduce peak ICU peak demands, the selected ORDSs were assigned to a specific OR and particular day during the cycle. Base on an LP formulation of this problem [8], all possible combinations of assignment of ORDS to a specific OR and a particular day were considered using computer modeling. The ICU bed demands of the resulting case schedule were calculated based on the ICU requirements of surgical cases performed in the previous cycles and surgical cases performed in current cycle. For this purpose, we used the mean ICU length of stay for each case type. See Fig. 1 for an example of how an MSS might be constructed. The computer-modeling package AIMMS (Paragon decision technology B.V., Haarlem, the Netherlands) was used to construct the MSS for both Erasmus MC and the virtual hospital.

Any surgical case that was not incorporated in an MSS was scheduled following the current Erasmus MC scheduling method, resulting in similar performance measures. The value of different MSSs was assessed by 2 outcome measures: the increase in OR utilization and the leveling of the number of ICU beds occupied by elective surgical patients. For both Erasmus MC and the virtual hospital, cycle periods of 1, 2, and 4 weeks were examined.

## 3. Results

Use of an MSS can improve OR utilization considerably by up to $6.3 \%$ point. Simultaneously, the ICU workload from such an MSS can be optimal leveled, resulting in less surgery cancellation and fewer ICU refusals. The length of a single MSS cycle has a strong influence on the obtainable improvement of OR capacity. In addition, the virtual hospital potentially has benefits more than the Erasmus MC does (Fig. 2).

Fig. 3 presents for the Erasmus MC a comparison of the ICU demand when it used an MSS, with a 2-week cycle period, compared to a situation when no MSS is used. Comparable results hold for other cycle periods of the Erasmus MC and the virtual hospital.


Figure 3: Number of occupied ICU beds by patients for which a surgical case was incorporated in an MSS with a cycle period of 2 weeks compared with an arbitrary chosen 2-week period (June 3, 2004, until June 16, 2004) in the Erasmus MC. Note that approximately $70 \%$ of the ICU demand of elective surgical patients is incorporated in the MSS (see Table 2).

Data analysis yields that the cycle period is important for the proportion of surgical cases incorporated in the MSS as well as that of total related ICU workload (Table 2). The MSSs for Erasmus MC incorporated fewer cases than that for the virtual hospital. In addition, shorter cycle periods resulted in smaller proportions.

## 4. Discussion

The aim of this study was to determine the benefits of an MSS in terms of improved OR utilization and leveling of ICU workload. Computational experiments showed for the Erasmus MC and a virtual hospital that a cyclic case schedule is indeed able to reduce peak demands on the ICU while at the same time increasing OR utilization. Apparently, the seemingly conflicting goals of efficiency and access to hospital services can be optimized simultaneously.

|  | Cycle period |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | 1 y | 4 wk | 2 wk | 1 wk |
| Proportion of surgical cases incorporated in an MSS (\%) |  |  |  |  |
| Erasmus MC | 100 | 53 | 42 | 27 |
| Virtual Hospital | 100 | 80 | 75 | 62 |
| Proportion of the ICU demand of surgical patients determined by an MSS(\%) |  |  |  |  |
| Erasmus MC | 100 | 45 | 38 | 17 |
| Virtual Hospital | 100 | 74 | 69 | 68 |

Table 2: Description of the influence of length of the cycle period on the proportion of surgical cases incorporated in an MSS and on the proportion of the ICU demand of surgical patients

Existing literature on surgical case and ICU scheduling is mostly concerned with scheduling of add-on cases, emergency cases, and allocation of OR and ICU time to departments [13-15]. Only a few authors have investigated the use of cyclic surgical case scheduling approaches [16-18]. None of them, however, proposes a case scheduling method that actually schedules individual surgical case types, accounts for uncertain case durations, and levels the associated workload on ICUs. Hence, MSSs described in this article enriches the available literature and available case scheduling methods.

We assumed that the Erasmus MC block planning method was used. This implies that OR time is reserved to deal with emergencies and to lower the risk on overtime. Hence, $100 \%$ utilization is not obtainable. A higher accepted risk on overtime results in a higher norm utilization. In combination with the assumption that surgical cases that were not incorporated in an MSS were scheduled following the current Erasmus MC practice, the potential improvement may therefore differ for other hospitals depending on their choice to accept overtime and their current OR scheduling practice.

Like the durations of surgical cases, length of stay on the ICU and surgical wards may be highly unpredictable, particularly in a tertiary referral environment. A system that guarantees no cancellation of surgical cases needs a considerable amount of reserve capacity [10]. Unless this capacity is available, leveling of bed requirements by taking into account mean length of stay reduces the probability of peak demands. This helps to reduce the number of case cancellation. An adequate registration system is therefore indispensable to predict surgical duration and bed usage. Note that leveling of ICU bed requirements only concerns the proportion of surgical cases incorporated in an MSS and that therefore the obtained benefits strongly depend on the proportion of ICU bed requirements incorporated in an MSS. The remaining part of the ICU bed requirements might be leveled according to other principles such as the method of Kim and Horowitz [19].

When a single surgical department schedules its patients independently from other departments, the result is a suboptimal schedule in terms of ICU demands and OR utilization. A more flexible hospital organization and cooperation between different surgical departments may further improve the surgical schedules in terms of OR utilization. An MSS as described in this article offers the opportunity to integrate such flexibility in the care pathway and hence optimize or utilization and level ICU demand.

The use of ORs by various surgical departments on the same day has large organizational implications such as the requirements for specialized equipment, multiemployable personnel in all ORs, and possibly longer changeover times. Moreover, the daily activities of clinicians are influenced by the unpredictable durations of surgical cases of other surgical departments. Operating room utilization is higher when surgical cases of multiple surgical departments can be scheduled in the same OR, on the same day [9]. A hospital should make a trade-off between OR utilization and the flexibility to schedule surgical cases from multiple specialties in the same OR on the same day. Nevertheless, a
cyclic planning approach that includes the use of an MSS is also applicable to a single surgical department.

Clinicians are responsible for the patient scheduling, which is a requirement for implementation. In addition, most clinicians already have a repetitive schedule. The same type of patients is every week operated on the same day. An MSS offers the opportunity to optimize OR utilization and level ICU bed requirement for all clinicians together. Therefore, it functions as communication tool between planners, clinicians, and other services within hospitals for which an MSS structures for example material coordination. Consequently, the week-to-week case scheduling requires less effort, and the administrative burden on medical staff is lowered because an MSS provides a substantial part of the final surgical schedule.

Our findings show that the proposed cyclic OR planning policy results in a leveled outflow of patients toward the ICU. Although in this study we have focused on reduction of surgical case cancellation because of ICU bed shortages, leveling of other resource requirements might be beneficial for other aspects of a hospital's organization, for example, required intraoperative navigation systems, numbers of fluoroscopy equipment, availability of beds on the ward, and fluctuations in the required number of postoperative computed tomography scans.

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## Chapter 6

## Implementing a master surgical scheduling approach in an acute general hospital

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## Chapter 6

# Implementing a master surgical scheduling approach in an acute general hospital 

Abstract


#### Abstract

A regional hospital in the Netherlands improved its performance by implementation of a cyclic and integrated surgical scheduling approach. This approach cyclically executes a master surgical schedule of surgery types and is dedicated to optimize operating room utilization, robustness, and overtime, while it also takes resource demand on other hospital departments into account, such as wards. Before 2007, the hospital faced severe problems, such as excessive underutilization of resources, huge budget deficits, and pressure on quality of care due to badly organized hospital logistics. Implementation of the surgical scheduling approach resulted in the first substantial organizational improvements in years. Hospital management obtained higher controllability of hospital logistics, while ward management reported substantial reduction in unforeseen fluctuations in bed occupancy. The study shows the added value of Operations Research models in hospital practice.


## 1. Introduction

The Netherlands face ageing population and rising health care costs, as most western countries do (OECD, 2008). At the same time, the public is more and more demanding for the latest technology, and short waiting and access times. The growing demand for cure and care provided by hospitals put a strong focus on their efficiency and efficacy. Hospital management has to deal with the seemingly conflicting objectives of low costs, high quality of care, and high quality of labor.

In most Dutch hospitals, physicians work on fee-for-service. Before 2004, the entire budget of a hospital was based upon contracts with the government and insurance companies. This generally put hospitals in a position where they had to manage budgetconstrained resources. Moreover, before 2008 all physicians were paid by a lump sum system, which provides income guarantee without much financial incentives to maximize patient throughput. Both systems severely restrict the flexibility of adjusting capacity to the actual demand in hospitals. Also, the system was highly driven by capacity supply instead of care demand. This in total resulted in high inefficiencies.

The Dutch government is currently changing the health care system in favor of a more market-oriented structure. This provides incentives to surgeons, anesthesiologists, and hospitals to work more efficiently. Beatrix Hospital (Gorinchem, The Netherlands) deliberately wants to improve their performance regarding efficiency and manageability of patient flows. One of its major challenges is to improve processes related to surgical case scheduling. Surgical scheduling is a complex task in hospitals, and a popular topic among academic researchers (Blake and Donald, 2002; Cardoen, et al., 2008; Carter, 2002;

Dexter, et al., 2004). Typically, the focus is on maximizing operating room utilization and revenues. However, an operating room department is not a stand-alone unit within a hospital. Reports on real implementations of strategies that optimize surgical scheduling in an integrated way with preceding and subsequent departments are scarce.

Beatrix Hospital successfully implemented a Master Surgical Scheduling (MSS) approach. This approach cyclically executes a master surgical schedule of surgery types. A master surgical schedule allows not only for optimization of operating room utilization, robustness, and overtime, but it also takes resource demand on other departments into account, such as wards. We describe in this article the implementation process and the reported benefits of the master surgical scheduling approach in the hospital. To position this process in a more theoretical context we start with an organizational approach on implementation problems in Section 2. We then introduce the case in Section 3, followed by a detailed discussion of the implementation in Section 4 of each of the seven steps of master surgical scheduling as they were introduced in Chapter 1.In Section 5 we present results. Section 6 discusses the implementation in Beatrix hospital. Finally we draw conclusions in Section 7.

## 2. Dealing with implementation problems: an organizational approach

Hospitals consist of organizational units that use both bureaucratic and professional forms of control (Georgopoulos and Mann, 1962; Lawrence and Dyer, 1983). The organizational culture and focus of these units influence many aspects of MSS implementation.

Organizational culture concerns norms, beliefs, and values (Peterson, 1979). In other words, it concerns the mindset of people working in an organization. Four different mindsets or worlds are distinguished in hospitals: care, cure, control, and community (Glouberman and Mintzberg, 2001a; b). Distrust amongst these four worlds makes health care a disconnected process.

Organizational focus of a unit/department depends on the patient groups treated and the treatments offered (Davidow and Uttal, 1989; Herzlinger, 1997). A focused unit is aimed at a limited number of patient groups and/or treatments. Next to general purpose units, we distinguish three types of focused units: specialty based, delivery based, and procedure based. In this section we describe the effects of each of these foci on the organizational culture and how prerequisites of implementing an MSS arise in each of these foci.

### 2.1. Specialty based focused units

Specialty based departments / units are aimed at a single patient group and offer almost all treatments for this group of patients. Examples in the literature are centers for cardiac care and centers for orthopedics (Casalino, et al., 2003; Herzlinger, 1997; Meyer, 1998). These
centers encompass all resources required for treatment. As resources in specialty based focused units are dedicated, surgeons have more control (Casalino, et al., 2003). We therefore expect organizational culture to highly value professional autonomy.

Successful implementation of MSS in specialty based focused units is also highly dependent on the degree of sub-specialization of surgeons, the volume of patients treated, and the case-mix. A high degree of specialization of surgeons, or high variety in case-mix, complicates defining surgery types, and makes implementing an MSS difficult. For such specialty based organizational units with high sub-specialization and high case-mix variety an MSS such as defined by Belien and Demeulemeester (2007) is more suitable. In general, an MSS can be successfully implemented in specialty based focused units with low sub specialization and in those units where a high sub specialization is combined with large patient volumes and moderate case mix variety.

### 2.2. Delivery based focused units

Delivery based organizational units are aimed at multiple patient groups, which require a similar type of treatment or type of care delivery. The main examples in the literature are ambulatory surgery centers (ASCs) (Casalino, et al., 2003; McLaughlin, et al., 1995; Yang, et al., 1992). ASCs offer ambulatory, or day-case, surgery and impose limitations on the maximum length of stay, complexity of the surgical procedures, and physical condition of patients. ASCs typically encompass both ORs and wards.

Delivery based focused units exhibit a culture of (strong) common goals related to the timeliness of the care delivery process (Yang, et al., 1992). For instance, the authors witnessed remarkable differences in punctuality of starting times of ORs between general purpose and delivery based focused units within a single hospital. While the delivery based (ASC) ORs almost always start on time, the general purpose ORs are on average 20 minutes late. These delays can not be explained by emergency or urgent cases. We argue that the difference in average starting time is the consequence of differences in organizational culture.

As multiple patient groups are treated, multiple specialties work in a delivery based unit. The unit's resources, therefore, must be shared between specialties. An MSS offers clear allocation criteria, and guarantees timely and sufficient capacities. In combination with the common goals in this type of unit, this stimulates cooperation between surgeons and personnel. Moreover, since delivery based focused units treat high volumes of patients with low case-mix variety, they are well suited for an MSS approach.

### 2.3. Procedure based focused units

Procedure based focused units are aimed at a single patient group and a single type of treatment. The best known example in the literature of a procedure based organization is
the Shouldice Hospital in Canada. Shouldice is aimed at the surgical treatment of hernia patients, and has adapted its processes and lay-out to the patient group treated (Heskett, 1983). Examples in the literature of procedure focused organizational units are ophthalmologic centers for cataract surgery (Schrijvers and Oudendijk, 2002).

Procedure based focused units exhibit an even stronger culture of common goals and values than delivery based units. Procedure based focused units treat large volumes of patients, with low case-mix variety and are, therefore, well-suited for MSS.

### 2.4. General purpose units

General purpose units are not aimed at specific patient groups or treatments. Typical examples are the OR department of a community general hospital, or a general ward. These units operate as shared resources, used by all specialties. Resource sharing might lead to conflicts between the four worlds in hospital care. Specialists might be tempted to cheat the system in their advantage, to ascertain required resources. The organizational culture is presumably weak. Whether an MSS approach is feasible for such general purpose units, therefore, strongly depends on case-mix variety, volume, the number of specialties, and the potential efficiency gain. MSS may offer allocation criteria to win support from surgeons, staff and management by creating insights in resource allocation and hereby offer financial control.

### 2.5. Implications for practice

Aside from general purpose organizational units, we discussed three different foci for organizational units and their effects on implementing an MSS approach. Hence, the suitability of MSS is affected by the organizational focus and culture, and the case mix characteristics that come with it.

We argued that implementing an MSS in a hospital consisting of focused organizational units with a low sub specialization of surgeons is relatively easy for a number of reasons. First, focused units exhibit a culture of common norms and beliefs. This culture enforces the willingness to cooperate between specialties, surgeons and personnel, and lowers distrust. Second, delivery and procedure based focused units treat larger numbers of similar patients. As a consequence, repetition is higher, which simplifies defining surgery types. Third, MSS offers clear allocation criteria for shared resources. Last, focused organizational units are, typically, easier to control. Focus thus reduces the managerial workload. Therefore, managerial attention can be paid to implementation of the MSS.

Hospitals with unfocused organizational units that want to implement an MSS might contemplate creating focused organizational units. Focus influences case-mix and volume characteristics of these units, and might thus improve the potential for the MSS
approach. Creating such an organizational structure, although requiring considerable efforts, might also further reduce the implementation prerequisites considering managerial control and data collection.

Even implementation of a planning approach that is well-equipped to deal with the characteristics of processes, cultures, and foci in hospitals is often hard. A considerable amount of leadership is required to overcome resistance from surgeons and staff against organizational changes. However, integration of the four worlds (Glouberman and Mintzberg, 2001a; b) and alignment of processes of different units potentially improves efficiency (Harper, 2002) to the extent that hospitals, in these times of costs reduction, have no other choice.

Hospitals that consist of focused units will benefit most from the advanced planning methods. Hospitals that not yet consist of focused units benefit from MSS implementation through the focusing that comes with the MSS concept. Implementation of an advanced planning approach such as MSS comes with several implementation issues. Particularly the availability of reliable data and weak cooperation between different actors in a hospital organization are of concern. The magnitude of the implementation issues depend on organizational foci and culture, and the inherent characteristics of the processes.

## 3. Case background

Beatrix hospital is a regional hospital that provides primary care. The hospital has annually approximately 10,000 hospital admissions. Total ward capacity is 329 beds. The hospital has two operating room locations where respectively five inpatient and three outpatient operating rooms are located. Beatrix Hospital is part of the Rivas Zorggroep that incorporates Beatrix Hospital, home care, elderly and nursing homes. Physicians in Beatrix hospital are private entrepreneurs who work fee-for-service.

Before 2007, Beatrix hospital faced severe problems due to badly organized hospital logistics. These comprise excessive underutilization of resources, huge budget deficits, and pressure on quality of care. As in most hospitals, surgical scheduling is a tedious task, performed by numerous people such as clerics, nurses, managers and surgeons. In Beatrix hospital this logistical process was strongly surgeon-oriented, and typically subject to fierce fights. The hospital had no proper managerial structure to discuss basic logistical measures such as utilization and overtime. Nobody had a clear overview of responsibilities. To make it even more complex, each department, and sometimes even among surgeons within a single department, were using different planning and scheduling guidelines and systems.

Within the chaotic situation of surgical case scheduling in Beatrix hospital, surgeons were the most influential actors who created maximum flexibility to adjust schedules whenever they wanted, for whatever reason. Surgical cases tended to be announced very shortly in advance by the surgeons, even the most elective cases. This
habit of late submissions resulted in little insight in the upcoming volume of inpatients at wards and other hospital resources. Generally, this resulted in overestimation of demand and hence higher costs. Moreover, the chaotic situation and the conflicts coming along with it, substantially lowered labor satisfaction of hospital employee.

Under Dutch law, employed staff has the right to be scheduled six weeks in advance. Whilst surgeons are self-employed, other hospital staff, such as operating room nurses, are not. Late changes such as cancellation of surgical patients hence generate high costs for the hospital that cannot timely reduce its amount of staff. In turn, late case submission could result in resource conflicts that cause delay, overtime and or cancellation of other elective patients.

The quality of care came under pressure due to the badly organized hospital logistics. The late announced admissions resulted in last-minute preparations causing higher fault rates, resulting in for example prolonged length of stay. In 2006, Rivas Zorggroep, owner of the Beatrix Hospital, changed hospital management to deal with all these urgent problems. Their objectives were to improve the financial situation, efficiency, and the chaotic planning and scheduling practice, particularly in relation to surgical inpatients. Hence, the organizational structure was to be changed such that resource utilization and throughput would increase. Moreover, due to the changes in the Dutch health care system since 2004, Beatrix hospital can now negotiate with health insurance companies on the revenues and volumes of Diagnostic Treatment Combinations (DTCs). To maximize benefits, Beatrix Hospital aims to control production of those DTCs that generate revenues to improve the financial situation.

## 4. Solving the surgical scheduling problem at Beatrix Hospital

Beatrix hospital's problem hence comprises of redesigning its surgical scheduling processes to improve efficiency and manageability. As such, an attempt can only be successful when surgeons are convinced that their patients are scheduled in time. We therefore introduced an approach that allows sufficient medical autonomy for surgeons to do so. Hence, scheduling of individual patients remains under the responsibility of surgeons.

Manageability concerns the ability to focus on the most beneficial surgical cases as well as the ability to organize stable patient flow through the hospital. In the field of industrial engineering, master production plans (for capacity) and master production schedules (for actual batches of items/patients) do so. When applied to operating room departments they are usually both called Master Surgical Schedule. To use the industrial engineering terminology we redefine the first as surgical block plan (Belien and Demeulemeester, 2007; Blake and Donald, 2002) and we call only the latter Master Surgical Schedule (van Oostrum, et al., 2008a; van Oostrum, et al., 2008b).

We define a master surgical schedule as a cyclic schedule repetitively executed on the level of individual surgical case types. It covers all frequent elective surgery types, levels the workload of other hospital departments, is robust against uncertainty, improves utilization rates, and maintains autonomy for surgeons. In the execution phase, actual patients are assigned to surgery types that build up the master surgical schedule. The logistical concept for operating room management that incorporates such a master surgical schedule is called a master surgical scheduling approach. Beatrix Hospital chooses this approach to solve its surgical scheduling related problems.

The model for the master surgical scheduling approach comprises of seven steps as defined by Van Oostrum et al. (2008a). First, a hospital defines the scope of the master surgical scheduling approach, i.e., the resources and departments to be included in the logistical improvement project. Second, reliable data on hospital processes needs to be gathered. In addition, the organizational structure and working needs to be adequately described. Third, capacity plans are made for all resources involved. Fourth, a set of recurrent surgery types needs to be defined that cover the surgical case mix of a hospital. Fifth, the actual master surgical schedule is constructed (van Oostrum, et al., 2008b). Sixth, patients are assigned to the surgery types in the master surgical schedule. Seventh, the master surgical schedule needs to be periodically revised to account for trends in patient arrivals, changes in waiting lists, and renewed contracts with health insurance companies.

Beatrix hospital started the implementation trajectory on April 1, 2007. Hospital management was involved together with a project leader, an internal business consultant, while no external business consultants were involved. There were weekly meetings between the project leader and representatives of the surgeons and managers of the operating room and wards to inform and discuss progress and intermediate results. An implementation trajectory typically is a process of going back and forward, where the


Figure 1: Overview landmarks and time periods of the different steps during the implementation of a master surgical scheduling approach in Beatrix hospital.
results in latter steps may cause the need to redo or refine earlier steps. Figure 1 shows per step the timeline of the project, including the most important landmarks. We will discuss each implementation step below and comment on our experiences during these steps.

### 4.1. Step 1: Scope of the MSS

Beatrix Hospital defined as implementation goal the improvement of operating room efficiency, stability of ward occupancy, and manageability of the planning and scheduling processes. Consequently, the capacity planning and operational scheduling of the operating room department, the wards, and the intensive care unit were involved. Due to the scope of these resources, the most important actors were operating room and ward managers, surgeons, and the hospital management. The need for efficiency and organizational improvement were very clear. This substantially helped the hospital management in convincing other actors. The main advantages for physicians were the reduction of cancellations and higher income. The latter was only possible since the last changes in the Dutch health care system. Ward management obtained benefits of improved labor satisfaction, while the hospital itself had reduced costs. These win-win situations were a prerequisite for implementation of the MSS approach. This step was officially finished after the first general meeting, including presence of most surgeons, about 6 weeks after the start of the project.

### 4.2. Step 2: Data gathering

At the start of the project it became clear that useful logistical information was fairly unavailable in Beatrix hospital. This complicated the project as we required basic data to perform calculations in order to optimize operating room efficiency and stability of ward occupancy. Required data comprised of data on patient level of all hospital admissions that include surgery, as well as data on the surgery itself. We used the year 2006 for analysis.

All data are entered by nurses and approved by physicians. Some delays in the project occurred due to the time needed to obtain data. Partly due to the database containing surgical information being maintained by a commercial company who was not willing to provide fast access to the data, partly due databases maintained by departments of Rivas Zorggroep that were generally unable to provide data quickly. After obtaining all patient data they were merged using Microsoft Access. Hence, we obtained a single database providing information about all patients that underwent surgery in 2006. In a similar way we obtained data on the availability of capacity during that year. We checked all data for inconsistency and verified the source of data.

Also, the organizational structure and the inherent difference in planning and scheduling processes were investigated. This showed that the tendency in Beatrix hospital was that planning and scheduling processes were surgeon-oriented. However, major
difference existed between surgical departments. For instance, surgeons of the department of General Surgery were highly specialized, while surgeons of the Gynecology department were generalists. Hence, it was required to deal with all kinds of different backgrounds to implement the MSS approach. The total data gathering was completed about five months after the start of the project.

### 4.3. Step 3: Capacity planning

Replanning capacity of the wards and operating rooms was started after the first data came available, approximately one month after the project start. It involved resource dimensioning and allocation within the constraints set by agreements on target production, and target utilization and availability of resources. These agreements are summarized in a norm-utilization (Van Houdenhoven, et al., 2007) of a particular user on a particular resource, e.g., the norm utilization of general surgery (user) of operating room capacity (resource) is $80 \%$. It also comprises of sufficient slack to deal with variability in resource demand.

Based upon previous experiences, Beatrix hospital identified 40 high-volume weeks and 12 low-volume weeks to account for holidays and reduced staff availability. Moreover, the hospital and the surgical departments expect the patient demand to grow annually by $3 \%$. We used the norm utilization, the identification of low and high-volume weeks, the expected growth, and organizational restriction as input to the capacity planning.

Basically, ward capacity is determined by the amount of available staff and not the amount of available physical beds. Ward management has a limited budget to hire extra staff at (very) short term. This is clearly to be minimized. A master surgical scheduling approach generates a stable flow of elective surgical patients and thereby lowers the expected need of additional staff. We determined the amount of required staff such that overall costs (including hiring extra staff) were minimal.

Analysis of the operating room data showed that $30.9 \%$ of the operating room budget was wasted.


Figure 2: Total number of assigned hours in block plan per week in Beatrix hospital in the year 2006. These hours are made available several weeks in advance to surgical departments to schedule surgical patients.

Furthermore, there existed a strong fluctuation in weekly operating room production (see figure 2). This causes strong fluctuations of demand at for example wards. This initial analysis was presented to representatives of all surgical departments on May 22, 2007.

Despite the initial fierce discussion, all actors, including surgeons, agreed that the current situation was unacceptable. The hospital and surgical departments agreed on an immediate capacity cut-down of about $20 \%$. Moreover, all actors accepted that it was required to re-define the operating room block plan that defines, weekly, which departments operates when and in which operating room. This is obviously a prerequisite to optimize the master surgical schedule to its full potential.

During reconstruction of the operating room block plan, surgeons and hospital staff came up with all kinds of restrictions. Clearly, this potentially reduced substantially the flexibility to change the capacity plan and thereby the potential efficiency gains. Such restrictions concerned for example weekly personal appointments and old privileges. The proposed requests were discussed with the project leader who had the final decision power to implement or refuse the requests for changes.

The initial operating room capacity cut-down was completed by September 2007, about five months after the project start. In total this step took much longer as it was necessary to change several times the operating room block plan to maximize the benefits of the master surgical schedule (see Step 5).

### 4.4. Step 4: Define a set of recurrent standard case types

Surgery types function as building blocks of a master surgical schedule. In Beatrix Hospital we defined surgery types separately for each surgical department as the operating room block plan identifies rooms dedicated to a particular department. We used a cluster method based on Ward's Hierarchical Cluster Method (Ward, 1963) to construct standard surgery types that minimize the variability in surgery duration, length of stay, and the portion of dummy surgeries. In addition to standard surgery types, dummy surgeries are needed to cover the surgical case mix uncovered by the standard surgery types. After constructing the initial set of standard surgery types, we discussed them with surgeons to determine their applicability. Some modifications were made such that surgeons could better identify themselves with the set of surgery types of their department. Before applying clustering, we identified 282 different surgical cases. These were finally brought down to 91 standard surgery types, including dummy surgery types.

After construction of the standard case types, the frequencies of some of them were adjusted. Beatrix hospital did so to improve market performance with regard to access times and aimed in this way to increase revenues. This was done particularly for cases belonging to DTCs that are subject to negotiations with insurance companies.

### 4.5. Step 5: Construction of the Master Surgical Schedule

In this step we scheduled surgery types, based upon their frequency, into the surgical block plan determined in Step 3 to obtain a master surgical schedule. We distinguished wards into a ward for inpatients from General Surgery and Gynecology, a ward for all remaining surgical inpatients, a ward for outpatients, and an intensive care unit. Scheduling was done so that the bed occupancy of each ward and patient outflow from the operating room towards each of the wards are stabilized.

To make a first version of the master surgical schedule we used linear programming techniques by Van Oostrum et al. (2008b). During discussions on the master surgical schedule with hospital staff and surgeons, many bottlenecks appeared that required changes in the schedule. Instead of programming all these additional constraints and objectives we adjusted the schedule manually and monitored the effect of these changes by comparing the performance of the new schedule with the initial one. In this way we were able to construct a near optimal schedule that had the support of all actors.

Step 3 and 5 were redone subsequently several times to make sure that the surgical block plan of step 3 did not substantially prevent optimization of the master surgical schedule in step 5. Constructing of the final version required about half a year, including discussion sessions with involved actors.

### 4.6. Step 6: Execute the Master Surgical Schedule

Orthopedic Surgery, ENT, and Eye Surgery started using the master surgical schedule about one year after the project start. After a patient receives an indication for surgery, he or she is assigned to a slot in one of the weeks ahead. Beatrix hospital currently uses a planning horizon of three weeks. When a patient cannot be assigned to an appropriate slot during this period, he or she will be assigned to a scheduled dummy surgery. Patient scheduling is done by administrative supportive staff at outpatient clinics or at the centralized patient administration department in Beatrix hospital. Thanks to the in advance preparation, the implementation start went smoothly.

### 4.7. Step 7: Update a Master Surgical Schedule

Variation in patient demand, organizational changes, changes in the medical staff, and new annual production agreements with health care insurances may cause the need to revise a master surgical schedule. Beatrix hospital continuously monitors the need for revision. A couple of months after implementation the waiting lists for certain surgery types disappeared. The lack of patients resulted in under utilization of resources and conflicts between anesthesiologists, who refused to work for half days, and surgeons, who wanted to operate on their patients. Analysis on the cause of the lack of patients showed that the
capacity plans of the operating room and wards one side and the capacity plans of the outpatient clinics on the other side are still not properly aligned. Beatrix hospital urgently works on this problem.

## 5. Results

Beatrix hospital considers the implementation of the MSS approach as a success, as both efficiency and organizational gains are realized. First, efficiency gains are obtained at the operating room department where the annual budget for operating room hours is reduced from 12,848 hours to 9,972 hours ( $22.4 \%$ reduction). Beatrix hospital operated on $7.7 \%$ more patients in 2007 when compared to 2006, using the same capacity as at the same time surgery duration decrease by $9.0 \%$.

The actual cost reduction was realized by lowering the amount of employed operating room staff. Second, the hospital reported efficiency gains obtained by substantial improvements of the insights in fluctuation of patient inflow and occupancy at wards. This resulted in less last-minute hiring of staff. Third, efficiency gains are realized by an increase of revenues by the increase of number of surgeries in 2007.

The organizational benefits are considered to be also substantial. Implementation of the MSS approach was used as a tool to redesign the hospital management, resulting in a much clearer managerial structure regarding capacity and financial management. Implementation showed the causes of badly adjusted plans and schedules. While in the past substantial amounts of overcapacity hid these causes and their resulting problems, implementation of master surgical scheduling showed both. Furthermore, implementation of the master surgical scheduling approach pushed communication between actors in Beatrix hospital, leading to easy forecasting and capacity planning on longer term. Moreover, thanks to the in advance adjustments of plans and schedules, fewer people are involved in the operational schedules, hence, substantially reducing the total time effort for planning and scheduling surgical processes.

## 6. Discussion

Results from implementing logistical models strongly depend on the involvement and focus of actors. Moreover, results are subject to unforeseen and temporal changes in patient mix and arrival patterns. The reported results are calculated for a period when the implementation was not yet completed. Hence, longer post-implementation analysis is required to determine the gains on long term. Current results show that the master surgical scheduling approach has the potential to change processes to reduce fluctuation in patients' volumes and improve efficiency and manageability.

It remains unsure whether implementing another logistical approach would have led to better, the same, or worse results. For a particular hospital this will probably remain
unknown. However, when a couple of different logistical approaches are implemented in multiple hospitals, meta-analysis may reveal advantages of one logistical approach in respect to the others. Until then, empirical evidence that shows which logistical approach outperforms the other remains unavailable.

Hospital management has taken the lead for implementation of an MSS in Beatrix hospital. This created a situation wherein surgeons, who work on a fee-for-service basis, possibly do not immediately have benefits while they are faced with reduced flexibility regarding patient planning. The lack of (financial) incentives for surgeons initially resulted in some resistance. Due to the system changes in the Dutch health care sector, surgeons nowadays are paid extra when more surgical cases are performed. The increase in the patient volume hence resulted in higher income and this solved the resistance from the surgeon adequately. Other hospitals might focus on creating these incentives first so that from the start on the benefits for all actors is clearer.

Beatrix hospital set up a new management information system that provides essential information regarding resource utilization, waiting lists, and volume forecasts that were previously unavailable. All information required for the MSS approach is provided to different actors and readily available to use. The information helped during discussions with surgeons on the actual improvements, and made them actually see that their patients are scheduled on time.

Using norm utilization for resources, the hospital created room for fluctuation and unforeseen events such as emergency arrivals. In addition, surgeons are able to schedule their patients in the MSS according to the medical requirements, while the secretary staff may take care of the remaining organizational work. Although the flexibility to plan the operating room has been reduced for surgeons, the medical autonomy of surgeons to schedule patients based on medical requirements remain unaffected for both elective as for emergency patients as sufficient flexibility remains at that point.

Beatrix hospital has a central administration department that does the administration of the surgical scheduling for some of the departments. Given a fully functional MSS there is no need to organize it this way. Since the communication and adjustment of capacity plans of different departments is done in the master surgical scheduling approach, surgical departments can simply assign patients to predetermined slots. This improves the communication with surgeons and reduces the number of information transfers. Moreover, the central administration department no longer needs a front office, resulting in additional cost savings.

## 7. Conclusion

Hospital management is enthusiastic because of increased operating room efficiency and higher predictability in patient flows. Moreover, the first substantial organizational improvements have been realized in years. This resulted in higher controllability of
hospital logistics, lower costs, and higher financial benefits. Longer post-implementation is required to back the claims of the hospital management by quantitative measures.

This study shows that implementation of the MSS approach leads to improvements, showing the efficacy of the academic logistical models in practice. By the actual implementation and the study of its side-effects we fill the gap between the academic logistical models and the hospital logistics in practice.

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## Chapter 7

## Requirements for a full service level agreement at an operating room department - a case study

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## Chapter 7

# Requirements for a full service level agreement at an operating room department - a case study 

Abstract:


#### Abstract

BACKGROUND: A university hospital aims to have a service guarantee to all elective surgical patients, meaning that all are treated on their scheduled day. To prevent excessive overtime and to ensure proper treatment of emergency patients, the hospital controls case scheduling of surgical departments. Each individual schedule for an operating room may obtain a service guarantee, given that it adheres to organizational conditions. We study when it is possible to give all case schedules service guarantee, despite the fact that some are not properly constructed according to hospital rules. METHODS: Computer simulation modeling was applied using two years of complete operating room data of Erasmus University Medical Center. Historical data were used to construct two sets of surgical schedules. One set including schedules that were properly constructed, patients at such schedules automatically obtain a service guarantee. And one set of schedules that were not properly constructed. We varied the number of properly constructed schedules to study the effect of having more or fewer schedules fulfilling the rules. We defined as main output parameters raw utilization, number of late finishing ORs, and cancellation rates. RESULTS: Utilization drops when more surgical schedules are properly constructed. The number of operating rooms running late remains more or less constant when only patients of properly constructed schedules obtain service guarantee. When all patients obtain service guarantee, the number of operating rooms running late substantially increases if the number of properly constructed case schedules decreases. CONCLUSION: In this study we determine that a full service guarantee at Erasmus University Medical Center is possible if nine or more out of twelve schedules are properly constructed. To keep efficiency high, we recommend striving to nine guaranteed schedules in Erasmus MC.


## 1. Introduction

Efficient use of expensive hospital resources such as operating room departments is nowadays of high interest (1-3). Erasmus University Medical Center (Erasmus MC) adopted a business model based on controlled surgical case scheduling (4). Basically this business model, called Guaranteed Operating Room, guarantees that all elective patients are served. Hence, the objective is to have no cancellation of elective patients on the condition that surgical schedules are properly constructed. Such schedules are referred to as guaranteed schedules. After introduction of this system, it appeared to be particularly hard in practice to get all surgical schedules guaranteed. Without all schedules guaranteed, Erasmus MC did still not have a guaranteed service to all its elective patients. Erasmus MC considers guaranteeing service to all elective patients if the number of guaranteed
schedules is equal to or bigger than a certain threshold number. We investigate in this paper the effect of such an additional rule.

The main inpatient OR department in Erasmus MC is run as a facilitating department that provides staffed and fully equipped ORs to various surgical departments. A block planning approach has been adopted in which blocks of OR time are made available to surgical departments in advance $(5,6)$. Departments may only assign patients to OR blocks that were made available to them. The OR business model furthermore incorporates annual management contracts specifying the yearly amounts of OR time available for each of the surgical departments. Capacity for emergency cases and uncertainty of case durations is accounted for by determining target OR utilizations, which is done for each surgical department independently (7). One of the conditions for a guaranteed schedule is that it must include a predetermined amount of free OR time, or "planned slack." Because capacity for emergency cases is assigned to surgical case schedules, Erasmus MC does not operate a dedicated emergency OR (8).

In summary, elective patients are guaranteed when scheduled of properly constructed surgical schedules that adhere to the following rules and guidelines (4):

1. Case schedules are submitted 2 weeks in advance;
2. OR time is used maximally and block times are not exceeded;
3. Elective cases are planned using historical mean case durations;
4. Planned slack is included to deal with emergency cases and variability of case durations.
The advantage for the surgical department is that the OR department guarantees the service to all scheduled surgical cases whatever occurs during a day. Moreover, consistently applying these rules helps surgical departments in their yearly contract negotiations with the hospital board on the amount of annual OR time.

The OR day coordinator in Erasmus MC does the scheduling of emergency patients and eventually the rescheduling of delayed elective patients. Upon arrival of an emergency patient an interval is determined by anaesthesiologists wherein the patient has to be operated on without increased morbidity or reduced probability of full recovery (9). Depending upon the determined interval, the OR day coordinator decides to either postpone an elective case to perform the emergency surgery first or to add the emergency surgery at the end of one of the elective surgical schedules. When the surgical schedules have obtained a guarantee, cancelling of elective patients is not an option, while this does remain an option to the OR day coordinator when some of the surgical schedules did not obtain a guarantee. The business model helps in reducing the emotional debate that can be present at the OR when discussing the scheduling of emergency cases and the cancelling of elective cases.

Evidently, adding emergency patients to surgical schedules while at the same time guaranteeing that all elective patients undergo surgery can cause substantial overtime.

Erasmus MC deals with this issue by hiring staff for late afternoon and evening shifts to ensure that there is no excessive overtime for shifts that started in the morning.

Erasmus MC is interested in the effect of guaranteeing all elective patients when only a part of the schedules fulfill the aforementioned rules since for good reasons surgical departments are not always able to fulfill all the rules. For instance, some surgical cases will in expectation take longer than any available block of regular OR time. Hence, they will never fit in a guaranteed schedule. Therefore, we answer the following research question: when is a full service guarantee possible in terms of efficiency, quality of care, and quality of labor given that not all surgical schedules adhere to the Guaranteed Operating Room rules? Moreover, we are interested in the optimal number of guaranteed schedules for Erasmus MC. In the study we assume that all kinds of administrative problems are solved, e.g., surgical schedules are handed in on time with the right information. The following main output measures are used: utilization rates, number of ORs finishing late, and cancellation rates.

## 2. Methods

Erasmus MC is a tertiary referral center that has maintained a database with information on all surgical cases since 1994. Information includes case duration, surgeon and surgical department involved, performed procedures within a case, patient arrival time, and composition of the surgical and anesthesia team present for each case. Anesthesia and surgery nurses prospectively collected these data, surgeons retrospectively approved all data.

Simulation was used as a tool for analysis because of its visual power and the ability to realistically represent surgical processes (10-12). We represented the OR department of Erasmus MC by 12 ORs including all its staff, and we modeled holding and recovery facilities with infinite capacity. All elective and emergency processes during day time were represented as well as the work floor coordination. The model was built in Tecnomatix Plant Simulation (Tecnomatix, Plano, TX, USA).

We defined three main output parameters, namely raw utilization, number of late finishing ORs, and cancellation rates. Raw utilization is defined as the sum of the elective and emergency case durations divided by the available regular capacity during working hours. The number of ORs finishing late is compared to the planned end of block and compared to the availability of OR teams. The cancellation rates are subdivided in the percentage of scheduled elective patients cancelled on the day and the percentage emergency patients that is safely delayed until a next day.

### 2.1. Modeling

The main inpatient OR department uses block plans that are fixed at least six weeks in advanced. These block plans are based upon annual capacity agreements between surgical departments and the board of directors. A block plan determines which ORs are allocated to a surgical department. We use in this study a most common block plan as is shown in Table 1. This includes all main surgical departments operating at the inpatient department. Other surgical departments that perform only rarely surgery are left out of consideration.

The ORs were assumed to be generic such that all surgical cases can be performed in any of the rooms. Moreover, we do not consider scheduling restrictions due to staff unavailability, nor do we consider change-over times and late-starts. We assume that all ORs have a regular capacity of 450 minutes per day (from 8.00 hours until 15.30 hours). In addition, to deal with overtime without paying excessive increased overtime wages Erasmus MC has allocated extra OR teams to run 4 ORs from 15.30 hours until 17.00 hours and 3 ORs from 17.00 hours until 20.00 hours.

We use empirical data to simulate the processes at the OR department. These data consist of all performed elective and emergency surgical cases during day time in the period January 2006 until December 2007 at the main inpatient OR at Erasmus MC. From all cases the realized duration is known. Moreover, from a substantial proportion of the elective cases the planned duration is known. The planned duration originates from the scheduling stage. At this stage, the planner obtains the mean duration of the previous 15 cases (surgeon-dependent), subsequently he may adjust this time for the specific case. We assumed that no biased prediction was made to obtain a guarantee at a schedule.

Information on late cancellation of elective patients at particular surgical schedules could not be obtained from the electronic databases. From practice it is known that this number is limited. Moreover, we cannot determine whether patients are operated

| Surgical department | Number of ORs | Planned slack per surgical <br> schedule (minutes) |
| :--- | :---: | :---: |
| General surgery | 3 | 40 |
| Gynecology | 1 | 23 |
| Ear-nose-throat surgery | 2 | 7 |
| Neurosurgery | 1 | 38 |
| Traumatology | 1 | 77 |
| Orthopedic surgery | 1 | 20 |
| Plastic surgery | 2 | 32 |
| Urology | 1 | 12 |
| Overall | 12 | 249 |

Table 1: median number of ORs on a regular work day allocated to a surgical department and the amount of slack to be planned at each schedule at the main inpatient department in Erasmus MC.
on in an OR that is different from the original scheduled OR. For experimental purposes, we assume that the realized surgical schedules do not differ from the planned schedules with respect to the set of cases that is performed.

### 2.2. Modeling elective surgical schedules

We assumed that all surgical schedules are handed in on time. Hence, we can now retrospectively check whether surgical schedules fulfill the aforementioned rules and should obtain service guarantee for all elective patients. Essentially, on basis of the rules, denoted in the Introduction, guarantee of schedules is obtained if and only if all surgical cases have a planned duration and the sum of the planned durations is less than the available capacity minus the planned slack applicable to the department that submits the schedule. The amount of planned slack is annually determined on the expected mean duration of emergency cases per OR during day time. The amount of planned slack to be planned in each schedule is given in the third column of Table 1.

We were able to construct two sets of schedules based upon the historical data. A first set consisting of schedules that should have obtained guarantee, a second consisting of schedules that should not have obtained guarantee. From the database we were able to reconstruct in total 3,818 guaranteed surgical schedules and 1,374 non-guaranteed surgical schedules. Table 2 provides an overview of the number of guaranteed and non-guaranteed schedules.

| Surgical department | Number of guaranteed <br> surgical schedules | Number of non-guaranteed schedules <br> Where all cases have a <br> planned duration | phot all cases have a <br> planned duration |
| :--- | :---: | :---: | :---: |
| General surgery | 879 | 247 | 95 |
| Gynecology | 315 | 5 | 29 |
| Ear-nose-throat surgery | 721 | 97 | 50 |
| Neurosurgery | 258 | 237 | 38 |
| Traumatology | 323 | 12 | 47 |
| Orthopedic surgery | 384 | 175 | 82 |
| Plastic surgery | 595 | 91 | 41 |
| Urology | 338 | 102 | 26 |
| Overall | 3813 | 966 | 408 |

Table 2: Overview of the number of guaranteed and non-guaranteed surgical schedules of the inpatient department of Erasmus MC in between 1-1-2006 and 12-31-2007.

### 2.3. Modeling emergency surgical cases

Erasmus MC does not use a dedicated emergency OR at its inpatient department. Instead, the OR day coordinator uses the planned slack and the slack that occurs due to early finishing of cases to schedule emergency patients. Anesthesiologists determine the maximum waiting time for a new emergency patient. Basically, four different categories are used. When a patient is classified in Category A this means that surgery is to be performed as quickly as possible because of serious life or limb threatening injuries. In practice this corresponds to a maximum waiting time of 30 minutes starting when a case is announced. Category B denotes those patients with an organ, limb, tissue, joint or transplant threatening injury who need to be operated on within one hour. Category C denotes patients who have a high risk of infection or diminished functioning of organ, limb or transplant who need to be operated on within 6 hours. Category D denotes those patients who need to be operated on within 24 hours to avoid increased risk. Although it is preferred to schedule Category D patients on the day of arrival the day coordinator may decide to schedule the patient the next day. In the latter case, it may replace a scheduled elective case depending on the available space in the surgical schedule. Table 3 gives the different proportions of emergency patients in each of the categories according to expert opinions.

From the data we obtained all emergency surgeries that arrived during day shifts in the period January 2006 - December 2007. This data includes the case duration and the time of arrival. We grouped together all patients that arrived on the same day. We had, however, no information of the emergency category of a particular patient nor did we have information about the expected duration. Therefore, we randomly assigned, based on averages as presented in Table 3, one of the categories to patients prior to the arrival at the OR. For the purpose of this simulation study we have chosen to take the expected duration equal to the realized duration. During the performance of simulation runs we randomly selected each day a group of emergency patients that arrived on a single day in the empirical data.

At Erasmus MC it is common practice that a surgeon that has non-OR duties is called in to perform an emergency case when none of the surgeons already operating has time to perform the case. Due to the large size of the hospital we do not consider availability of surgeons as a restriction.

| Emergency Category | Percentage |
| :---: | :---: |
| A | 5 |
| B | 5 |
| C | 35 |
| D | 55 |

Table 3: Proportion of emergency patient categorized in the different categories based upon expert opinions.

### 2.4. Modeling the OR day coordination

At Erasmus MC an OR day coordinator does the work floor management. Besides all kinds of other tasks, to ensure that OR processes run smoothly, the day coordinator is responsible for deciding whether or not an elective case has to be cancelled to avoid overtime, moreover he is responsible for scheduling emergency cases. For these purposes the day coordinators uses the Guaranteed Operating Room set of rules. We describe the working of these rules more elaborately below.

During a working day, the coordinator continuously keeps track of the expected unused time in ORs. At the start of the day this is determined by the difference between the sum of the planned duration of elective cases and the available time ( 450 minutes). Upon completion of a case, the unused time is adjusted according to the difference in the planned and the realized duration of an elective case. Note that the planned slack is no longer relevant on the day of execution where it is replaced by the amount of unused time.

The day coordinator allows all cases belonging to guaranteed schedules to be executed, regardless of whether the expected completion time is later than 15.30 hours. Moreover, all firstscheduled elective cases of all nonguaranteed surgical schedules are allowed to start up. For all other (second, third, etc.) cases of non-guaranteed schedules the day coordinator recalculates the expected completion time based upon previously performed elective and emergency cases. Those cases of non-guaranteed schedules that are now expected to be completed after 15.30 hours are cancelled. See Figure 1 for a graphical representation.

Emergency cases belonging to Category A (maximum waiting time 30 minutes) are scheduled at the OR that comes first available. Cases that belong to


Figure 1: Decision flow diagram for checking whether an elective case is allowed to start.
either Category B or C are scheduled at an OR of the surgical department where they belong to if this OR comes available within the maximum waiting time and if sufficient unused time is left over at that OR. Otherwise, the day coordinator will find the ORs that come available within the accepted maximum waiting time and chooses from these the OR that has the largest unused time. When none of the ORs comes available within the maximum waiting time the day coordinator schedules the patient in the OR that comes first available. Emergency cases belonging to Category D are scheduled in the OR that has the largest amount of unused time, given that this amount is more than the case duration. When a day coordinator expects a Category D case to take longer than any of the amounts of unused capacity the case is postponed to the next day.

### 2.5. Scenario modeling

To investigate the effect of guaranteeing surgical schedules we conducted computer simulation experiments. The effect of guaranteeing surgical schedules was investigated by increasing the number of guaranteed surgical schedules in steps of two. Each experiment was subsequently repeated by guaranteeing service to all elective patients, using the same set of schedules. Hence, after an experiment in which only guaranteed service was available for patients at for example 4 out of 12 schedules, the experiment was repeated by assuming that service was guaranteed to all patients. This makes it possible to study the effect of guaranteeing service to all surgical schedules while the schedules themselves would not have obtained guarantee.

We conducted a preliminary experiment to determine an appropriate number of repetitions for the experiments. For this purpose we used the experiment of 8 guaranteed schedules where we guarantee only elective patients scheduled of the guaranteed schedules. This initial experiment had a run length of 100 working days. Using Law and Kelton (13) we determined the number of repetitions such that with $90 \%$ certainty (a) the absolute error of the mean utilization is less than $0.5 \%$, (b) the absolute error of the mean number of late finishing ORs is less than 0.1 , and (c) the absolute error of the elective cancellation rate is less than $0.5 \%$. The minimum number run length that fulfilled these constraints was 959 working days. We have chosen to use 1,000 working days for the simulation experiments.

The numbers of available guaranteed and non-guaranteed surgical schedules from the database are insufficient to perform simulation runs of 1,000 working days. We randomly duplicated schedules until the required number of guaranteed or non-guaranteed surgical schedules was obtained. We have grouped the emergency patients per day. During a simulation run we randomly selected the arrival pattern of one of these days.

We fixed for each number of guaranteed schedules the surgical department supplying such guaranteed schedules. Given a certain number of guaranteed schedules,
$\left.\begin{array}{ccccccccc}\hline \begin{array}{c}\text { Total number of } \\ \text { guaranteed } \\ \text { schedules }\end{array} & \begin{array}{c}\text { Type } \\ \text { composition }\end{array} & \begin{array}{c}\text { General } \\ \text { surgery }\end{array} & \text { Gynecology } & \begin{array}{c}\text { Ear-nose- } \\ \text { throat } \\ \text { surgery }\end{array} & \begin{array}{c}\text { Neuro- } \\ \text { surgery }\end{array} & \begin{array}{c}\text { Trauma- } \\ \text { tology }\end{array} & \begin{array}{c}\text { Orthopedic } \\ \text { surgery }\end{array} & \begin{array}{c}\text { Plastic } \\ \text { surgery }\end{array} \\ \hline 0 & \text { All Urology }\end{array}\right]$

Table 4: Scenario overview, the scenarios are referred to as a combination of the number of guaranteed schedules and the type of composition ( $\min =$ minimum amount of planned slack, $\max =$ maximum amount of planned slack, and $M L=$ most likely combination). The numbers represent the number of guaranteed surgical schedules in a particular scenario.
there are many combinations to form these schedules assuming the OR block plan (see Table 1). We have chosen to use the most likely combination of guaranteed surgical schedules, which is based upon the relative frequency of guaranteed schedules per department in the available database (see Table 2).

As a sensitivity analysis we adopt two other variants where the second is a combination of guaranteed schedules such that the amount of planned slack is maximized. The third variant is a combination of guaranteed schedules in which the amount of planned slack is minimized. See Table 4 for an overview of all scenarios.

## 3. Results

Figure 2 presents the mean utilization rate for the most likely set of guaranteed surgical schedules. The figure shows that the utilization of the OR department decreases when more schedules are guaranteed. Moreover, guaranteeing all elective patients in respect with only those patients at guaranteed schedules results in substantially higher utilization rates, which is beneficial for the hospital.


Figure 2: Raw utilization rate for different numbers of guaranteed schedules.


Figure 3: Mean number of ORs finishing after 15.30 hours, for different numbers of guaranteed schedules.

Figure 3 shows the mean number of ORs finishing after 15.30 hours. Remarkably, the number of ORs finishing late when only elective patients of guaranteed schedules are guaranteed is on average always lower than 4 , which is the number of available OR teams after 15.30 hours. The results furthermore show that the number of late finishing ORs is substantially higher when service to all elective patients is guaranteed. When eight or fewer case schedules are guaranteed, the mean number of late finishing ORs is higher than the availability of extra OR teams.


Figure 4: Mean number of OR teams finishing late. The extra teams are accounted for.


Figure 5: Percentage of working days that at least one OR team is working in overtime.
In Figure 4 the mean number of OR teams that have to work in overtime is addressed and in Figure 5 we present the percentage of working days that at least one OR team has to work in overtime. Herein we accounted for the extra OR teams, available after 15.30 hours. The numbers of teams working in overtime remains constantly low when only elective patients at guaranteed schedules are guaranteed. However, from Figure 4 and 5 it becomes clear that guaranteeing all elective patients with only a minority of the schedules being guaranteed leads to substantially more teams working in overtime.

Table 5 presents the percentage of emergency patients that are postponed to the next day, the percentage of emergency patients that is treated too late, and the cancellation

|  | Number of <br> guaranteed <br> schedules | Percentage of emergency <br> cases delayed to a next <br> working day | Percentage of <br> emergency cases <br> too late | Cancellation rate <br> of elective cases |
| :---: | :---: | :---: | :---: | :---: |
|  | 0 | $14.9 \%$ | $1.5 \%$ | $12.8 \%$ |
| Not | 2 | $15.1 \%$ | $1.5 \%$ | $10.3 \%$ |
| guaranteeing | 4 | $14.9 \%$ | $1.6 \%$ | $9.7 \%$ |
| all elective | 6 | $15.0 \%$ | $1.9 \%$ | $8.5 \%$ |
| patients | 8 | $15.4 \%$ | $1.7 \%$ | $6.4 \%$ |
|  | 10 | $15.8 \%$ | $1.8 \%$ | $2.8 \%$ |
|  | 12 | $17.2 \%$ | $1.9 \%$ | $0 \%$ |
|  | 0 | $14.9 \%$ | $1.9 \%$ | $0 \%$ |
| Guaranteeing | 2 | $15.8 \%$ | $2.1 \%$ | $0 \%$ |
| all elective | 6 | $16.2 \%$ | $1.9 \%$ | $0 \%$ |
| patients | 8 | $16.4 \%$ | $2.2 \%$ | $0 \%$ |
|  | 10 | $16.4 \%$ | $2.0 \%$ | $0 \%$ |
|  | 12 | $17.4 \%$ | $2.0 \%$ | $0 \%$ |

Table 5: Simulation results of quality of care parameters for scenarios in which the set of guaranteed schedules is based upon the "most likely variant".
rate of elective patients. The results show that there is hardly a relation between on one hand the percentage of emergency patients delayed to the next day and the percentage of emergency patients that are operated on too late and on the other hand the input of surgical schedule plus whether or not all elective patient are guaranteed. There exists a clear difference in the cancellation rate between guaranteeing all elective patients and guaranteeing only those of the guaranteed schedules. A substantial number of elective patients are cancelled in the latter case, particularly when the number of guaranteed schedules is low.

The sensitivity of the results for the input set of guaranteed schedules is given in Table 6. We investigated the effect of the input on utilization, the number of late finishing ORs and the cancellation rate of elective cases. The results show that the sensitivity is relatively low. All trends remain visible.

## 4. Discussion and Conclusion

In this paper we investigated the effect of guaranteeing the service to elective surgical cases. To answer when a full service guarantee to elective patients is possible we analyzed two alternatives. In the first, service was only guaranteed to elective patients on properly constructed, so-called guaranteed, surgical schedules. In the second alternative, the service to all elective patients was guaranteed. The effect was measured by utilization, number of late finishing ORs, and cancellation rates of emergency and elective patients. When

|  | Number of guaranteed | Mean utilization |  |  | Mean number of ORs |  |  | Cancellation rate of elective |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Max | ML | Min | Max | ML | Min | Max | ML | Min |
| Not guaranteeing all elective patients | 0 | 88.6\% | 88.6\% | 88.6\% | 3.7 | 3.7 | 3.7 | 12.8\% | 12.8\% | 12.8\% |
|  | 2 | 88.0\% | 87.1\% | 82.8\% | 3.7 | 3.5 | 2.9 | 11.7\% | 10.3\% | 11.6\% |
|  | 4 | 86.3\% | 84.3\% | 83.0\% | 3.6 | 3.2 | 3.0 | 10.0\% | 9.7\% | 8.3\% |
|  | 6 | 84.4\% | 83.7\% | 82.4\% | 3.3 | 3.2 | 2.9 | 6.5\% | 8.5\% | 6.6\% |
|  | 8 | 83.6\% | 80.6\% | 80.3\% | 3.3 | 2.8 | 2.7 | 4.6\% | 6.4\% | 3.3\% |
|  | 10 | 83.8\% | 80.0\% | 78.7\% | 3.3 | 2.8 | 2.6 | 0.6\% | 2.8\% | 1.4\% |
|  | 12 | 78.0\% | 78.0\% | 78.0\% | 2.6 | 2.6 | 2.6 | 0\% | 0\% | 0\% |
| Guaranteeing all elective patients | 0 | 102.3\% | 102.3\% | 102.3\% | 6.3 | 6.3 | 6.3 | 0\% | 0\% | 0\% |
|  | 2 | 100.4\% | 97.8\% | 95.9\% | 6.0 | 5.6 | 5.4 | 0\% | 0\% | 0\% |
|  | 4 | 96.8\% | 94.6\% | 92.6\% | 5.5 | 5.2 | 4.7 | 0\% | 0\% | 0\% |
|  | 6 | 90.6\% | 92.7\% | 89.8\% | 4.5 | 4.9 | 4.3 | 0\% | 0\% | 0\% |
|  | 8 | 87.6\% | 87.8\% | 83.4\% | 4.1 | 4.2 | 3.3 | 0\% | 0\% | 0\% |
|  | 10 | 84.4\% | 83.3\% | 79.9\% | 3.4 | 3.4 | 2.8 | 0\% | 0\% | 0\% |
|  | 12 | 78.0\% | 78.0\% | 78.0\% | 2.6 | 2.6 | 2.6 | 0\% | 0\% | 0\% |

Table 6: Sensitivity of the simulation results for changes in the set of guaranteed schedules.
applying service guarantee to only those patients of guaranteed schedules we found that more guaranteed schedules lead to a lower raw utilization, fewer ORs running late, and a lower cancellation rate of elective patients. Moreover, when all elective cases are guaranteed the utilization and the number of ORs running late are higher compared to the previous alternative. The number of cancellation and lateness of emergency patients appeared to be relatively indifferent for the number of guaranteed schedules. We recommend keeping the mean number of ORs running late below the number of available teams after 15.30 hours. Hence, full service guarantee is possible when nine or more schedules are guaranteed. Otherwise, service guaranteed should only be given to patients on guaranteed schedules. Since utilization drops when more schedules are guaranteed and treatment of emergency patients is indifferent for the number of guaranteed schedules, the optimal number of guaranteed schedules is nine at Erasmus MC.

We have chosen to use a fixed block plan that is based upon capacity agreements made between the surgical department and the board of directors. In practice, the number of ORs in use by the various departments may slightly differ from the block plan we assumed. In addition, the set of guaranteed schedules that are supplied are likely to differ from the "most likely" set of guaranteed schedules in the simulation study. However, results are either indifferent under the various settings or show a dependency on the number of guaranteed schedules. These trends remain visible when the set of a fixed number of guaranteed schedules was varied. Hence, we do not expect that changes in the OR block plan and the set of guaranteed schedules have a large impact on the decision when to guarantee all elective patients given a certain amount of properly constructed schedules.

The day coordinator has in practice the ability to reschedule elective patients during the day. The availability of surgeons mainly determines to which extent rescheduling is possible. We have not incorporated the rescheduling since we expect the impact to be similar for all scenarios. However, incorporating rescheduling might improve the results and may allow guaranteeing all elective cases having fewer case schedules guaranteed.

One of the major challenges of surgical case scheduling at Erasmus MC is to get surgical departments handing in case schedules according to the rules. First of all case schedules are often initially submitted incompletely. While the day coordinator may only require that information is complete at a very late moment, for the OR department as a whole it is better to have time to prepare the execution of the schedule. For instance material coordination and scheduling of X-ray equipment require in advance preparation. Leaving such administrative issues aside, surgical departments may argue that others have to hand in schedules that can be guaranteed since they themselves cannot. This can be advantageous since more patients can be scheduled while they still have the guarantee that all cases are performed. However, typically all surgical departments argue in the same way, leaving the OR with surgical schedules that do not fulfill the Guaranteed Operating Room rules. This potentially brings back the emotional discussions that surround the late cancellation of elective case in the OR. However, agreeing in advance on guaranteeing service to all elective patients if and only if more than nine schedules fulfill the rules moves the discussion forward in time and out of the OR.

OR staff may perceive "technical" overtime not always as overtime. In Erasmus MC OR staff is paid an extra 30 minutes to clean ORs after 15.30 hour. When an overtime of less than 30 minutes occur the OR staff working in that room will leave the cleaning tasks for the night shift and will hence not perceive overtime, although this is technically the case. This organizational flexibility possibly changes the number of rooms that need to be guaranteed for a full service concept. In Erasmus MC the number of required rooms changes from at least 9 to at least 5 guaranteed rooms.

Guaranteeing service to elective patients in other hospitals may work out as well as it does for Erasmus MC. The Guaranteeing Operating Room approach does not require a full redesign of the planning processes. Using historical schedules and data a hospital can determine the effect of guaranteeing schedules and service to elective patients.

Providing a service guarantee to customers of hospitals has a price. Surgical departments together with the OR should determine when a total service guarantee is acceptable for all actors involved in surgical case scheduling. The tradeoff between output measures such as utilization, overtime, and cancellation rates should function in this process as input to assist decision making. The size of a hospital and the availability of OR teams during and after day time determine the actual tradeoffs in different hospitals. In this study we determine that a full service guarantee is possible if nine or more out of twelve
schedules are properly constructed. Given that the utilization rate drops when more schedules are guaranteed, at Erasmus MC nine is the best number of guaranteed schedules.

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## Chapter 8

## Closing emergency operating rooms improves efficiency

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## Appendix to Chapter 8: <br> Letter 1: non-patient factors related to rates of ruptured appendicitis (Br J Surg 2007; 94: 214-221).

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## Chapter 8

# Closing emergency operating rooms improves efficiency 


#### Abstract

Long waiting times for emergency operations increase a patient's risk of postoperative complications and morbidity. Reserving Operating Room (OR) capacity is a common technique to maximize the responsiveness of an OR in case of arrival of an emergency patient. This study determines the best way to reserve OR time for emergency surgery. In this study two approaches of reserving capacity were compared: (1) concentrating all reserved OR capacity in dedicated emergency ORs, and (2) evenly reserving capacity in all elective ORs. By using a discrete event simulation model the real situation was modelled. Main outcome measures were: (1) waiting time, (2) staff overtime, and (3) OR utilisation were evaluated for the two approaches. Results indicated that the policy of reserving capacity for emergency surgery in all elective ORs led to an improvement in waiting times for emergency surgery from $74( \pm 4.4)$ minutes to $8( \pm 0.5)$ min. Working in overtime was reduced by $20 \%$, and overall OR utilisation can increase by around $3 \%$. Emergency patients are operated upon more efficiently on elective Operating Rooms instead of a dedicated Emergency OR. The results of this study led to closing of the Emergency OR in the Erasmus MC (Rotterdam, The Netherlands).


## 1. Introduction

Postponing emergency surgery may increase a patient's risk of postoperative complications and morbidity. Waiting times depend on the speed at which an operating room (OR) can organize its resources to operate upon an emergency patient. A common approach to deal with emergency procedures is to reserve OR capacity; this is believed to increase responsiveness to the arrival of an emergency patient [1, 2].

There are two basic policies for reserving OR capacity for emergency patients: in dedicated emergency ORs or in all elective ORs. The first policy, reserving capacity in dedicated emergency ORs, would combine short waiting times with low utilisation of expensive OR capacity. Hence, it is an expensive option, since one or more entire ORs cannot be used for elective surgery. Emergency patients arriving at a hospital that has adopted the first policy will be operated immediately if the dedicated OR is empty and will have to queue otherwise, whereas patients arriving at a hospital that has adopted the second policy can be operated once one of the ongoing elective cases has ended. Other planned cases will then be postponed to allow the emergency operation. Thus, besides influencing waiting times of emergency patients, the choice of either policy will have impact on the amount of overtime and OR utilisation.

Little evidence is available on the performance in terms of waiting times, OR utilisation, and overtime for the policy of reserving capacity for emergency patients in all
elective ORs. In this study we determined the best policy to reserve time for emergency patients. We assessed the policies using a discrete-event simulation model for this purpose.

## 2. Data and methods

Erasmus MC with 1,300 beds is the largest teaching hospital and tertiary referral centre in the Netherlands. It provides for the complete spectrum of surgical procedures, including transplantation and trauma surgery. Of the 34,500 admissions per year, some 20,000 involve a surgical procedure. Data on more than 180,000 surgical procedures have prospectively been collected since 1994, including procedure duration, the procedure name, the procedure type (elective or emergency), and surgical specialty involved. Data had been approved immediately after the surgical procedure by the surgery or anaesthesia nurse. The duration of surgical procedures, both emergency and elective, is assumed to be lognormal [3]. Table 1 shows the aggregate descriptive statistics of the central OR department of the Erasmus MC.

A block planning approach to schedule the elective procedures was assumed [4, 5]. We assumed that on average 12 ORs per day, five days per week were staffed and available. The availability of the staffed ORs was limited to 450 min per day. Moreover, all ORs were assumed to be multi-functional, i.e., all procedures types can be performed in all ORs.

We developed a discrete event simulation model [6, 7], using the simulation software tool eM-Plant (Plano, USA). This simulation model was a representation of the Erasmus MC 12 OR set-up. We simulated days independently of each other. In the first emergency policy, with emergency capacity allocated to one dedicated emergency OR, the remaining free OR time is allocated to exclusively elective ORs. In the second policy, with emergency time allocated to each elective OR, the reserved OR time is distributed evenly over all elective ORs. Figure 1 illustrates these policies.

| Description | Number |
| :--- | :--- |
| Number of different surgical procedure types | 328 |
| Mean number of elective cases per day | 32 |
| Mean case duration (minutes) | 142 |
| Standard deviation of the case duration (minutes) | 45 |
| Mean number of emergency cases per day | 5 |
| Mean emergency case duration (minutes) | 126 |
| Standard deviation of emergency case duration (minutes) | 91 |

Table 1: Aggregate descriptive statistics of the OR in Erasmus MC


Figure 1: Visualization of the two studied policies for allocating reserved OR time
A schedule with elective surgical cases is the input for the simulation model. These schedules are constructed by applying a first-fit algorithm [8]. The first-fit algorithm subsequently assigns for each surgical department separately surgical cases to the first available OR. The resulting surgical case schedule specifies therefore for each OR the elective surgical procedures to be performed. Procedures are planned using their mean duration, based upon the available data.

The given elective OR program forms the starting point for the comparison. We model the duration of elective producers by a procedure-specific lognormal distribution. Emergency patients arrive according to a Poisson process (with mean inter-arrival time of $1 / 5$ day): inter-arrival times are mutually independent and exponentially distributed. The duration of emergency surgery was based upon one lognormal distribution for all emergency procedures together. Emergency operation is on a first-come-first-served basis and is performed either after the first completion of an elective operation or at the emergency OR, depending on the policy adopted. Each specialty in Erasmus MC reserves one surgeon for emergency surgery. In practice, that particular day this surgeon has no outpatient clinics, teaching activities, or scheduled elective surgery, but typically administrative and research activities. We modelled no delay in starting emergency surgery due to surgeon or OR staff unavailability. We modelled no delay in starting emergency surgery due to surgeon or OR staff unavailability. Elective procedures planned in an OR are postponed until after the emergency operation and might be executed in overtime.

Overtime is defined as the time used for surgical procedures after the regular block time has ended. Efficiency of OR utilisation is calculated as the ratio between the total used operating time for elective procedures and the available time. The sequential procedure [9] to determine the run length of the simulation with a maximum deviation $10 \%$ and a reliability of $90 \%$ yielded a run length of 780 days, which includes approximately 4,000 emergency patients.

## 3. Results

Waiting times are plotted cumulatively in Fig. 2. In policy 1, with use of a dedicated emergency OR, all 4,000 emergency patients were operated on within 7 h . The mean waiting time was 74 ( $\pm 4.4$ ) min. In policy 2 , with capacity for emergency surgery allocated to all elective ORs, all 4,000 emergency patients were operated upon within 80 min . The mean waiting time was $8( \pm 0.5)$ min.

Table 2 shows values for the other two performance indicators broken down for type of policy. Efficiency of OR utilisation computed for all ORs in the first policy is $74 \%$; for the second policy it is $77 \%$. Overall, the second policy, with emergency capacity allocated to all elective ORs, substantially outperforms the first policy, with a dedicated emergency OR, on all outcome measures.

## 4. Discussion

This study showed that reserving capacity for emergency surgery in elective ORs performs better than the policy of a dedicated OR for emergency procedures in a large teaching hospital, based on a discrete-event simulation study with the three performance indicators: waiting time, overtime, and cost effectiveness of the OR.

The policy of allocating OR capacity for emergency surgery to elective ORs requires the OR department to be flexible. Upon arrival of an emergency patient, one of the ORs will have to fit the emergency operation into the elective OR schedule. The patients originally planned will have to be operated on either in another OR or at a later time. This requires flexibility of OR staff and surgeons in dealing with and accepting frequent changes to the original elective surgical case schedule. Also it requires OR to be equipped for all kinds of emergency surgery. Although OR departments that have physical overcapacity, i.e. OR departments where in general some of the ORs are unused, do not face this problem as they may allocate the emergency patient to an empty room that is sufficiently equipped. This way the OR staff have to move to this room, but not all rooms need to be fully equipped for all emergency surgery.

| Emergency policy: | Policy 1 | Policy 2 |
| :--- | :--- | :--- |
| Total overtime per day (hours) | 10.6 | 8.4 |
| Mean number of ORs with overtime per day | 3.6 | 3.8 |
| Mean emergency patients' waiting time (minutes) | $74( \pm 4.4)$ | $8( \pm 0.5)$ |
| OR utilization $^{\text {a }}$ (\%) | 74 | 77 |

$a$ The OR utilisation is the ratio of elective surgery hours performed and the available capacity

Table 2: Overview results of the outcome measures

Interrupting the execution of the elective surgical case schedule for emergency patients may substantially delay elective cases. However, inpatients are typically admitted to a ward before they are brought to the OR. Although delay due to emergency arrivals may cause inconvenience of patients it does not disturb processes in the OR.

Besides reserving OR capacity for emergency patients, ORs generally need to reserve capacity to cope with the variability in the session durations. In the elective policy, reservation might be shared to increase the flexibility for dealing with unexpected long case duration and emergency surgery, whereas the dedicated policy does not offer the opportunity to use this overflow principle.

In OR departments that have dedicated emergency ORs it is common practice to re-assign staff to elective ORs to deal with temporary staff shortages. Hence, upon arrival of an emergency patient, the team may be incomplete, which implies the patient must wait until the team is complete again, typically when one of the ongoing elective cases ends. This practice considerably reduces the advantage of a dedicated OR.

A dedicated emergency OR may cause queuing of emergency patients, confronting OR management and surgeons with the question which patient should be operated on first. Since such decisions are typically based on medical urgency, trauma procedures or a ruptured abdominal aneurysm will often be given preference over, for instance, fracture surgery. Hence, surgeries of specialties with less acute cases are more likely to be postponed. This would be less so if capacity for emergency surgery were to be allocated to all elective ORs, providing for various emergency patients to be operated on simultaneously.

Implementation of the policy by which emergency capacity is reserved in all elective ORs, requires all stakeholders on the OR to strictly adhere to the policy. In fact, the surgical departments that use a single OR face the so-called prisoner's dilemma. A single surgical department may benefit from not reserving capacity for emergency surgery, whereas this is disadvantageous for all surgical departments together. If one or more


Figure 2: Cumulative percentage of emergency patients in the two studied policies, treated within a certain (waiting) interval
surgical departments do not reserve free OR capacity on their own ORs and hence must use reserved capacity of other specialties, the latter face the prisoner's dilemma. Successful implementation, therefore, would require dedication of all surgical departments.

In this study we have chosen to adopt discrete-event simulation to assess both policies, while application of queuing theory might have been another method to compare both policies. Application of queuing theory to the problem at hand is, however, not straightforward due to the probability distribution of surgery duration. Further, ongoing research might show application of queuing theory to the problem addressed in this paper.

In conclusion, we have compared two policies to reserve OR capacity for emergency surgery. Results obtained from a discrete-event simulation study show that distribution of free OR capacity evenly over all elective ORs performs better than dedicated ORs on measures reflecting quality of patient care, staff satisfaction, and costeffectiveness. The policy of reserving free capacity can be successfully implemented on ORs only if all stakeholders were to participate. Moreover, besides the quantitative benefits as shown in this paper, it offers several, more soft advantages to improve ways of dealing with the variability that is inherent to medical processes.

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## Appendix to Chapter 8

## Letter 1: non-patient factors related to rates of ruptured appendicitis (Br J Surg 2007; 94: 214-221)

## Sir,

The authors established a positive correlation between higher rates of ruptured appendicitis and hospitals that have high volume of patients, many competing resources that are used efficiently, and no designated operating room (OR) for urgent surgical cases. Based on the authors' article we suspect that the hospitals' case-mixes cause the different rates of ruptured appendicitis. A hospital with a complex patient mix possibly acquires a relatively large number of severe ill patients who do already have ruptured appendicitis at admission. In our opinion a designated OR for acute cases is not the optimal business model to provide acute care, because a designated OR is inefficient, and because once the designated OR is occupied none of the other ORs is readily available.

The question to be answered is: how to deal with urgent surgical cases if a hospital with a complex patient mix is efficiently organised? Erasmus University Medical Centre in Rotterdam, the Netherlands has adopted a business model in which OR capacity is efficiently used and where no designated trauma team is available. Upon arrival of an urgent patient, the patient is brought into an empty operating room and helped by staff of the OR that finishes first. To prevent overtime and to operate acute surgery spare capacity is allocated in all elective schedules1,2. Analysis in a forthcoming paper shows that in Erasmus University Medical Centre more than $80 \%$ of the urgent cases were started within 30 minutes after consultation of the Anaesthesiologist in-charge. Hence, without a designated OR for urgent surgery acute care can be provided efficiently and accurately3.

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## Chapter 9

## A simulation model for determining the optimal size of emergency teams on call in the operating room at night

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## Chapter 9

# A simulation model for determining the optimal size of emergency teams on call in the operating room at night 

Abstract


#### Abstract

BACKGROUND: Hospitals that perform emergency surgery during the night (e.g., from 11:00 PM to 7:30 AM) face decisions on optimal operating room (OR) staffing. Emergency patients need to be operated on within a predefined safety window to decrease morbidity and improve their chances of full recovery. We developed a process to determine the optimal OR team composition during the night, such that staffing costs are minimized, while providing adequate resources to start surgery within the safety interval. METHODS: A discrete event simulation in combination with modeling of safety intervals was applied. Emergency surgery was allowed to be postponed safely. The model was tested using data from the main OR of Erasmus University Medical Center (Erasmus MC). Two outcome measures were calculated: violation of safety intervals and frequency with which $O R$ and anesthesia nurses were called in from home. We used the following input data from Erasmus MC to estimate distributions of all relevant parameters in our model: arrival times of emergency patients, durations of surgical cases, length of stay in the postanesthesia care unit, and transportation times. In addition, surgeons and OR staff of Erasmus MC specified safety intervals. RESULTS: Reducing in-house team members from 9 to 5 increased the fraction of patients treated too late by $2.5 \%$ as compared to the baseline scenario. Substantially more OR and anesthesia nurses were called in from home when needed. CONCLUSION: The use of safety intervals benefits OR management during nights. Modeling of safety intervals substantially influences the number of emergency patients treated on time. Our case study showed that by modeling safety intervals and applying computer simulation, an OR can reduce its staff on call without jeopardizing patient safety.


## 1. Introduction

Nighttime surgical schedules allow for fewer surgical cases than daytime surgical schedules. Irregular-hour payments and work-sleep regulations for operating room (OR) staff contribute to higher costs during the night. Facing OR staff shortages, OR suite managers must critically appraise nighttime workforce deployment (1).

Appropriate size of the emergency team, with acceptable frequency of calling team members from home, should ensure sound treatment for all patients. Previous studies show that analytical methods can help determine numbers of OR and anesthesia nurses needed (2-7). It has been shown that the labor costs of emergency teams during regular hours, second shifts, and weekends can be significantly reduced, but most authors exclude the night shift ( $7-9$ ), or focus on single specialty OR suites ( $2-4$ ). These studies implicitly assume that all patients are operated upon at the time that they were actually scheduled for surgery, without considering the option of postponing surgery within a predefined safety
interval. For example, a facility may consider it imperative for a patient with a ruptured abdominal aortic aneurysm to be operated on within 30 min of arrival, while a patient with an amputated finger should be operated on within 90 min of arrival, and a patient with a perforated gastric ulcer should be operated on within 3 h of arrival. Although studies have defined safety intervals for emergency surgery during the day (10), the option of postponing operations by a safe time interval during the night shift has not yet been addressed.

Dexter and O'Neill propose a statistical method to determine the weekend staffing requirement of the OR suite (7). It assumes an expected workload and computes the staffing requirements based on this workload. However, it does not incorporate safety intervals that might level the workload, hence reduce numbers of staff to be called in from home.

Tucker et al. proposed a queuing approach to determine OR staff requirements (6). This approach does not address the issue of treating patients on time. In addition, the authors do not incorporate detailed characteristics of surgical departments and the OR suite. This approach, therefore, typically over-estimates the probability of multiple cases being performed at the same time, since no delaying of cases within their safety intervals was considered. The method, just like that of Dexter et al. (11) is deliberately conservative.

Our study was designed to determine optimal OR staff on call at nights by explicit modeling of patients' safety intervals and by discrete-event simulation modeling. The simulation model provided insight into the trade-off between the main outcome measures of providing surgery on time and calling in team members from home. A case study was performed for the main OR suite of Erasmus Medical Center Rotterdam (Erasmus MC).

## 2. Methods

Erasmus MC is a tertiary referral center that has maintained a database with information on all surgical cases since 1994. The information includes duration of the various cases, the surgeon and surgical department involved, the exact nature of the cases, patient arrival time, and the composition of the surgical and anesthesia team present for each case. Anesthesia and surgery nurses prospectively approved these data immediately after a surgical case and surgeons retrospectively approved all data.

In this study we used a discrete simulation model to determine the optimal size of emergency teams (i.e., anesthesia and surgery nurses) on call at night. The model involves several issues already addressed by others, including sequencing of emergency patients 12 and determination of staff requirements $(2,3,13)$. Our novel contribution is the additional modeling of medically sound safety intervals for emergency patients.

In anticipation of emergency cases, anesthesia and surgery nurses are on call either in the hospital or at home. For this study, the hours from 11:00 PM through 7:30 AM were defined as the night shift. We included the six surgical departments that yearly
performed at least eight cases during the night shift. These are listed in Table 1, including data on surgical cases and intensive care unit (ICU) requirements.

We used simulation as a tool for analysis because of its ability to incorporate uncertain operating times and "what if" scenario analyses ( $10,14-16$ ). Several earlier studies have used simulation successfully to assess the effects of staff reduction on patients' waiting times or staff requirements $(2,3,12,13,17)$. The model was built in eMPlant (Tecnomatix, Plano, TX) and comprised the following elements: (a) holding room, (b) ORs, (c) recovery room, (d) anesthesia nurses (either at home or in the OR suite) (e) surgery nurses (either at home or in the OR suite), and (f) patients.

Waiting times for emergency patients and the frequency of calling OR and anesthesia nurses from home were the primary outcome measures in this study. These measures combined with information on number of nurses on call in the hospital, provided insight into the costs of night shifts and the corresponding waiting time of emergency patients.

### 2.1. Modeling

The model started at the beginning of the night shift with an empty recovery room and no patients waiting for emergency surgery (i.e., an empty holding room). Recovery room capacity is unlikely to be a bottleneck in the process, since patients recovering from earlier evening shift cases are typically taken care of by evening shift nurses or recovery nurses. Hence, the assumption of an empty recovery room was valid. The model allowed for the possibility that evening shift cases (i.e., before 11:00 PM) were continuing after start of the

| Surgical department | Proportion of all surgical cases (\%) | Duration of surgical case (min) |  | Proportion of ICU <br> patients (\%) |
| :---: | :---: | :---: | :---: | :---: |
|  |  | Mean | Variance |  |
| General surgery ${ }^{a}$ | 47.1 | 156.16 | 118.45 | 15.6 |
| Traumatology ${ }^{\text {b }}$ | 15.9 | 146.14 | 82.10 | 2.7 |
| Neurosurgery | 15.5 | 126.24 | 72.32 | 28.6 |
| Plastic surgery | 9.9 | 200.32 | 142.45 | 10.6 |
| Gynecology | 7.2 | 74.05 | 41.02 | 3.7 |
| ENT surgery ${ }^{\text {c }}$ | 4.4 | 90.21 | 54.88 | 10 |

[^0]Table 1: Data per surgical department over all night shifts in the period 1994-2004 at the main OR suite of Erasmus MC
night shift. We modeled this by assuming that at the start of the night shift there was a $40 \%$ likelihood that one OR was occupied and an $18 \%$ likelihood that two ORs were occupied, based on our case mix data. Remaining times of the surgical cases running into the night shift were drawn from a lognormal distribution based on the same case mix data. Of course, these probabilities apply to Erasmus MC and should be adjusted by readers using numbers suitable for their facility.

We assumed that emergency patients arrive according to a Poisson distribution, which was modeled time-dependent. Table 2 shows the assumed inter-arrival times for each of the night shift hours, also expressed as mean number of patients arriving in a particular hour. Furthermore we assumed that each patient was instantly available for surgery (i.e., essential tests or scans already having been performed).

The type of surgical cases determined the composition of the team required to be present. At Erasmus MC, a large team of two anesthesia nurses and three surgery nurses is used for complex procedures (e.g., liver transplantation) and for unstable trauma patients. Other cases are staffed with one anesthesia nurse and two surgery nurses. Table 3 shows the proportion of cases requiring a large team for each surgical department. We did not incorporate anesthesiologists and surgeons in the model, since we assumed an adequate staffing of anesthesiologists and surgeons.

Upon arrival of a patient, the simulation checked the availability of ORs and the presence of the emergency team members. If both were available, the patient was operated on immediately. If too few emergency team members were available within the safety interval, the additional members were called in from home. Travel time was taken to be 30 min. We assumed that once assigned to a case, a nurse would be occupied for its duration.

| Hour of the <br> night shift | Inter-arrival times <br> in minutes | Expressed in mean number <br> of per hour |
| :---: | :---: | :---: |
| $11: 00 \mathrm{pm}-0.00 \mathrm{am}$ | 175 | 0.34 |
| $0.01 \mathrm{am}-1.00 \mathrm{am}$ | 204 | 0.29 |
| $1.01 \mathrm{am}-2.00 \mathrm{am}$ | 520 | 0.12 |
| $2.01 \mathrm{am}-3.00 \mathrm{am}$ | 656 | 0.09 |
| $3.01 \mathrm{am}-4.00 \mathrm{am}$ | 1386 | 0.04 |
| $4.01 \mathrm{am}-5.00 \mathrm{am}$ | 1782 | 0.03 |
| $5.01 \mathrm{am}-6.00 \mathrm{am}$ | 1386 | 0.04 |
| 6.01 am-7.00 am | 891 | 0.07 |
| 7.01 am-8.00 am | 1040 | 0.06 |
| Mean number of patients per | - | 1.1 |
| night |  |  |

Table 2: Mean inter-arrival time of emergency patients during the night shift

Case durations were drawn from lognormal distributions (18) for the surgical departments involved, based on the data set of the case under consideration (Table 1). After completion of the surgical case, team members called in from home were assumed to leave if no other patients were waiting or if the patients waiting did not require their attendance. Patients at this point were assigned to the ICU or the recovery room, given the probabilities in Table 1. Time needed to

| Surgical department | Percentage |
| :--- | :---: |
| General surgery $^{a}$ | 30.0 |
| Plastic surgery | 35.4 |
| Neurosurgery | 0.0 |
| Traumatology $^{b}$ | 20.0 |
| Gynaecology $^{c}$ | 17.0 |
| ENT surgery $^{c}$ | 0.0 |
| $a$ Including vascular and transplant surgery. $_{l}^{b}$ Including emergency orthopedic surgery. |  |
| $c$ Ear nose throat surgery. |  |

Table 3: Proportions of surgical cases requiring a large emergency team bring a patient to the ICU and to return to the OR was taken to be 30 min , which reflects an upper bound on transportation time during nighttime.

One anesthesia nurse assisting in the case transported the patient to the recovery room. There, at least two anesthesia nurses watched patients through the night, as required by Dutch Anesthesiology recommendations. If only one anesthesia nurse was assisting surgery and the recovery room was previously empty, the second nurse was called in from home on time, i.e., 30 min before the end of surgery. The recovery duration was drawn from a lognormal distribution using a historical mean of 70.2 min and a variance of 37.0 min . The surgery nurses were assumed to clean the OR and to restock materials after the surgical case. Figure 1 schematically depicts the simulation model.

We determined four safety intervals based on clinical experience of the surgeons and OR staff in Erasmus MC. Then, based on a surgical department's patient mix and types of the cases we determined proportions of patients to be assigned to each of the four safety intervals. Table 4 shows these safety intervals for the six Erasmus MC surgical departments involved.


Figure 1: Concept process diagram of the simulation model.

| Safety intervals | General <br> surgery $^{a}$ | Plastic <br> surgery | Neurosurgery | Traumatology $^{\boldsymbol{b}}$ | Gynecology ENT surgery ${ }^{\boldsymbol{c}}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $1 .<30 \mathrm{~min}$ | 15 | 0 | 74 | 15 | 26 | 33 |
| $2 .<90 \mathrm{~min}$ | 25 | 32 | 14 | 17 | 18 | 6 |
| $3 .<3 \mathrm{~h}$ | 20 | 18 | 10 | 24 | 21 | 29 |
| $4 .<8 \mathrm{~h}$ | 40 | 50 | 2 | 44 | 35 | 32 |

${ }^{a}$ Including vascular and transplant surgery.
${ }^{b}$ Including emergency orthopedic surgery.
${ }^{c}$ Ear nose throat surgery.
Table 4: Proportions of emergency patients per surgical department assigned to the four safety intervals

### 2.2. Precalculations

To benchmark results from the discrete-event simulation model we used the method developed by Dexter and O'Neill. 7 Calculations were based on results from the staffing scenario that represented the current practice (Scenario 1, Table 5). This scenario was assumed "safe," seeing that in the past 10 yrs no emergency patients have been in severe danger because of OR staff shortage or lateness. Simpler methods such as Dexter and O'Neill's (7) will reveal whether an OR suite acts on rational grounds.

Under Dutch Law, a nurse in-house during night shifts is paid $7.5 \%$ of the regular hourly daytime wage, while a nurse on call is paid $6 \%$ of the regular hourly daytime wage. A nurse working during the night shift is paid $47 \%$ more than the regular hourly daytime rate. Travel times of nurses on call are considered to be working time.

### 2.3. Scenarios

To evaluate compositions of emergency teams, we defined nine scenarios. Current practice in Erasmus MC (Scenario 1, Table 5) was used as the reference scenario against which we evaluated the other eight scenarios. In each subsequent scenario, one nurse was excluded from the night shift or placed on call at home instead of being present at the hospital.

| Scenario | $\mathbf{1}$ | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ | $\mathbf{5}$ | $\mathbf{6}$ | $\mathbf{7}$ | $\mathbf{8}$ | $\mathbf{9}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Number of anesthesia nurses <br> (in-house + on call at home) | $4+1$ | $3+1$ | $3+1$ | $2+2$ | $3+1$ | $2+2$ | $2+2$ | $2+1$ | $2+1$ |
| Number of surgery nurses (in- <br> house + on call at home) | $5+1$ | $5+1$ | $4+1$ | $4+1$ | $3+2$ | $3+2$ | $2+2$ | $2+2$ | $2+1$ |

Table 5: Scenarios of emergency team compositions

Scenarios with fewer staff than available in Scenario 9 were not considered, since these resulted in excessive waiting time for emergency patients.

We performed sensitivity analyses on the safety intervals. This allows comparison of our discrete- event simulation model with existing methods that do not deploy patient safety intervals. Five alternatives were analyzed. Each was constructed by excluding one or more safety intervals. The proportion of patients previously assigned to these intervals was distributed among the remaining safety intervals according to the original ratios. The following alternatives were defined:

1. Excluding safety intervals of 8 h ;
2. Excluding safety intervals of 3 and 8 h ;
3. Excluding safety intervals of $90 \mathrm{~min}, 3$, and 8 h ;
4. Excluding safety intervals of 30 min ;
5. Excluding safety intervals of 30 min and 90 min .

Further sensitivity analyses were performed on the likelihood of recovery occupancy at 11:00 PM, the arrival intensity of patients during the night, and the likelihood of occupied ORs at 11:00 PM. We evaluated the following alternatives:
6. Likelihood of $50 \%$ recovery occupancy at 11:00 PM.
7. $-10 \%$ arrival intensity
8. $-20 \%$ arrival intensity
9. $-30 \%$ arrival intensity
10. $+10 \%$ arrival intensity
11. $+20 \%$ arrival intensity
12. $+30 \%$ arrival intensity
13. $+25 \%$ likelihood of occupied ORs at 11:00 PM.
14. $+50 \%$ likelihood of occupied ORs at 11:00 PM.
15. $-25 \%$ likelihood of occupied ORs at 11:00 PM.
16. $-50 \%$ likelihood of occupied ORs at 11:00 PM.

Based upon preliminary experiments we tested the alternatives for Scenarios 1 and 6 . These two scenarios represented the interval from which Erasmus MC was likely to select its staffing level.

Before conducting the experiments, the model was validated by comparing the output of scenario 1 with actual practice. The key validation measure was number of times anesthesia or surgery nurses were called from home. Validation was provided by this number in the model being the same as in practice.

The number of runs required to obtain reliable results was determined by the following equation:

$$
n_{r}^{*}(\gamma)=\min \left\{i \geq n: \frac{t_{i-1,1-\alpha} \sqrt{S^{2}(n) i}}{|\bar{X}(n)|} \leq \gamma\right\}
$$

Where $n_{r}^{*}(\gamma)$ is the minimum number of runs for obtaining a relative margin of error of $\gamma$, given an average value of $\bar{X}(n)$. The value $S^{2}(n)$ represents the variance of $\bar{X}(n)$ and $\alpha$ is the probability distribution of $t$, which is set at 0.05 . A relative error of 0.1 , which is a common value in simulation studies, yields 10,000 days (19). To measure patients' safety, we categorized amounts of time exceeding the safety interval in four categories: 0 to 10,11 to 20,21 to 30 , and more than 30 min after the safety interval.

## 3. Results

The method of O’Neill and Dexter (7) applied to Scenario 1 showed that Erasmus MC could safely reduce the number of anesthesia nurses by one. The resulting staffing level guarantees that in $95 \%$ of all night shifts sufficient staff are available using the actual times that patients waited for surgery. Reducing the number of anesthesia nurses by one yields Scenario 2. Applying the simulation methods, as presented in this paper, will achieve an additional reduction in the number of surgery nurses by letting patients wait longer for surgery, but not so long as to exceed the safety intervals.

Table 6 presents proportions of patients treated too late during the night shift. These computational results show a steady increase in total percentage from Scenario 1 (current situation) to 6 . Scenarios 7, 8, and 9 show substantial increases in numbers of patients treated more than 30 min late. Reducing the numbers of anesthesia and surgery nurses following Scenarios 1 to 6 only slightly increases the proportion of patients treated too late. For instance, in Scenario 6 the percentage of patients treated 30 min after their safety intervals has increased by $2.5 \%$ relative to Scenario 1 ( $1.4 \%$ vs $3.9 \%$ ). Correspondingly, the total percentage of patients treated too late has increased by only $2.3 \%$ in Scenario 6 ( $10.6 \%$ vs $12.9 \%$ ).

Compared with the baseline Scenario the hospital can reduce overall staffing levels by one anesthesia nurse and one surgery nurse. In addition, Scenario 6 shows that one more anesthesia and one more surgery nurse can be allocated to take call from home instead of being in-house. Compared with Scenario 2 (outcome of method from O'Neill and Dexter7), Scenario 6 shows that Erasmus MC could reduce the overall staffing level

| Safety interval | SC1 (\%) | SC2 (\%) | SC3 (\%) | SC4 (\%) | SC5 (\%) | SC6 (\%) | SC7 (\%) | SC8 (\%) | SC9 (\%) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Total too late <br> Between 0 min and 10 min <br> too late | 10.6 | 11.2 | 12.7 | 12.6 | 12.9 | 12.9 | 15.5 | 17.0 | 23.1 |
| Between 10 min and 20 min <br> too late | 2.9 | 2.8 | 2.8 | 2.7 | 2.8 | 2.8 | 2.6 | 2.3 | 2.2 |
| Between 20 min and 30 min <br> too late | 3.1 | 2.0 | 3.1 | 3.1 | 3.2 | 3.2 | 3.0 | 2.6 | 2.3 |

$\mathrm{SC}=$ scenario.
Table 6: Proportions of emergency patients treated too late


Figure 2: Proportions of nights in which the first nurses are called in from home.
by one surgery assistant. The extra reduction in overall staffing levels by our simulation method compared with the method of O'Neill and Dexter is due to the delay of some emergency patients within their safe waiting interval.

Figure 2 shows percentages of nights the first anesthesia nurse and the surgery nurse are called in from home in the different scenarios. Figure 3 shows this for the second nurses. The frequencies increase significantly beyond Scenario 4, then sharply decline for Scenario 9. In this scenario significantly more patients are postponed to the day team.

Tables 7 and 8 show the results of the sensitivity analyses. The sensitivity analysis in Scenario 3 (SA3) shows that setting all safety intervals to 30 min leads to a substantial increase of patients treated too late. In addition, SA1 to SA5 show that results are sensitive


Figure 3: Proportions of nights in which the second nurses are called in from home.
to the use of safety intervals. Accepting longer waiting times for all patients (SA4 and SA5) leads to a decline in the percentages of patients treated outside their safety intervals (Table 7). Occupancy of the recovery room at 23:00 h increases the number of patients who are treated late (SA6). Furthermore, outcomes are insensitive to variation in arrival intensity (SA7-SA12), but are sensitive to the number of occupied ORs at 23:00 h (SA13SA16).

| Reference scenario | Safety interval | SA: Varying safety intervals |  |  |  |  | $\begin{gathered} \hline \text { SA: Rec } \\ 23.00 \mathrm{~h} \\ \text { SA6 (\%) } \\ \hline \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | SA1 (\%) | SA2 (\%) | SA3 (\%) | SA4 (\%) | SA5 (\%) |  |
| SC1 | Total too late | 12.0 | 12.8 | 23.3 | 7.8 | 3.4 | 13.4 |
| SC1 | Between 0 min and 10 min too late | 3.2 | 3.5 | 4.8 | 2.2 | 1.1 | 1.7 |
| SC1 | Between 10 min and 20 min too late | 3.5 | 3.8 | 5.8 | 2.8 | 1.1 | 4.2 |
| SC1 | Between 20 min and 30 min too late | 3.5 | 3.5 | 6.5 | 2.1 | 1.1 | 5.6 |
| SC1 | More than 30 min too late | 1.8 | 2.0 | 6.1 | 0.7 | 0.1 | 1.9 |
| SC6 | Total too late | 14.6 | 15.5 | 27.4 | 9.6 | 4.5 | 15.6 |
| SC6 | Between 0 min and 10 min too late | 3.1 | 3.3 | 3.9 | 2.3 | 1.3 | 1.3 |
| SC6 | Between 10 min and 20 min too late | 3.5 | 3.8 | 5.0 | 2.7 | 1.3 | 4.1 |
| SC6 | Between 20 min and 30 min too late | 3.4 | 3.5 | 5.8 | 2.4 | 1.5 | 5.9 |
| SC6 | More than 30 min too late | 4.6 | 4.9 | 12.7 | 2.1 | 0.4 | 4.3 |

SC = scenario; SA = sensitivity analysis; Rec $23.00 \mathrm{~h}=$ recovery room occupancy at 23.00 h .
Table 7: Proportions of emergency patients treated too late given various sensitivity analysis scenarios

|  |  | SA: varying arrival intensity during the night |  |  |  |  |  | SA: likelihood of occupied ORs at 23.00 h |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Reference scenario | Safety <br> interval | $\begin{gathered} \hline \text { SA7 } \\ (\%) \end{gathered}$ | $\begin{gathered} \hline \text { SA8 } \\ \text { (\%) } \end{gathered}$ | $\begin{gathered} \hline \text { SA9 } \\ (\%) \end{gathered}$ | $\begin{gathered} \hline \text { SA10 } \\ \text { (\%) } \end{gathered}$ | $\begin{gathered} \text { SA11 } \\ (\%) \\ \hline \end{gathered}$ | $\begin{gathered} \text { SA12 } \\ \text { (\%) } \end{gathered}$ | $\begin{gathered} \text { SA13 } \\ \text { (\%) } \end{gathered}$ | $\begin{gathered} \text { SA14 } \\ \text { (\%) } \\ \hline \end{gathered}$ | $\begin{gathered} \text { SA15 } \\ (\%) \end{gathered}$ | $\begin{gathered} \text { SA16 } \\ (\%) \end{gathered}$ |
| SC1 | Total too late | 10.6 | 10.4 | 10.4 | 11.9 | 11.7 | 11.7 | 9.7 | 13.2 | 7.5 | 15.1 |
| SC1 | Between 0 min and 10 min too late | 3.0 | 2.7 | 2.8 | 3.2 | 3.0 | 2.9 | 2.4 | 3.6 | 1.9 | 3.9 |
| SC1 | Between 10 min and 20 min too late | 3.3 | 3.4 | 3.2 | 3.3 | 3.5 | 3.2 | 2.9 | 3.8 | 2.3 | 4.3 |
| SC1 | Between 20 min and 30 min too late | 3.1 | 3.2 | 3.1 | 3.4 | 3.4 | 3.3 | 2.9 | 3.9 | 2.0 | 4.6 |
| SC1 | More than 30 min too late | 1.2 | 1.1 | 1.3 | 2.0 | 1.9 | 2.3 | 1.6 | 1.9 | 1.3 | 2.2 |
| SC6 | Total too late | 12.7 | 12.4 | 12.2 | 14.3 | 14.6 | 14.8 | 11.7 | 15.6 | 9.4 | 17.8 |
| SC6 | Between 0 min and 10 min too late | 3.0 | 2.6 | 2.8 | 3.0 | 3.0 | 3.0 | 2.3 | 3.6 | 1.9 | 3.8 |
| SC6 | Between 10 min and 20 min too late | 3.3 | 3.3 | 3.1 | 3.4 | 3.6 | 3.2 | 2.8 | 3.8 | 2.5 | 4.3 |
| SC6 | Between 20 min and 30 min too late | 3.3 | 3.2 | 3.3 | 3.4 | 3.3 | 3.4 | 2.9 | 3.8 | 2.2 | 4.7 |
| SC6 | More than 30 min too late | 3.2 | 3.2 | 3.0 | 4.4 | 4.6 | 5.2 | 3.6 | 4.4 | 3.0 | 5.0 |

Table 8: Proportions of emergency patients treated too late given various sensitivity analysis scenarios

## 4. Discussion

A simulation model was used to determine optimal size of the emergency team on call during the night, i.e., from 11:00 PM through 7:30 AM, using safety intervals for emergency patients. The main contribution of this study is that it combines aspects of patient safety, uncertainty of the case duration, and nocturnal OR staffing in a simulation approach. $2,7,20$ Although this is a single center study, variation of the input parameters showed that the approach can be generalized for use in other centers. To implement this approach, hospitals need to obtain data on patient arrival rates and safety intervals. Frequencies per safety interval can be computed by each surgical department.

The case study indicated that staffing, and thus cost, reductions may be realized for night shifts without jeopardizing patient safety. This is best illustrated in Scenario 6, which yields reduction of two in-house surgery nurses and two in-house anesthesia nurses as compared with Scenario 1. The consecutive Scenarios 7 to 9 , with even greater reduction, are associated with substantial increase of patients being treated too late. The choice for Scenario 6 potentially makes two OR and two anesthesia nurses available for the daytime surgical schedules. Overall this would increase the productivity of the OR suite. Historically, the main OR suite in Erasmus MC deployed four anesthesia nurses and five surgery nurses during the night shift, forming two emergency teams permanently present in the OR suite. Statistics over the past 4 yrs, however, indicate a structural overcapacity of these teams. In $45 \%$ of the night shifts, no new patients were admitted for surgery after 11 Pm . On average, 1.1 patients per night were operated on. In one of every seven nights, two teams had to work simultaneously to perform all emergency surgeries on time. Adopting the method of O'Neill and Dexter7 would have led to a change from Scenario 1 to Scenario 2, corresponding to an annual saving of approximately $€ 70,000$. Using a simulation approach, including the use of safety intervals, showed that changing from Scenario 1 to Scenario 6 in. Erasmus MC is safe. Moreover, this reduction allows cutting night-shift costs by approximately $24 \%$, corresponding to an annual cost reduction of $€ 245,000$. The cost reduction is calculated by the same cost parameters used in the precalculations plus additional saving due to the increased availability during daytime of teams on call from home.

Sensitivity analyses (SA1-SA5) showed the impact of safety intervals. Tucker et al. (6) implicitly assumed that all cases start immediately, while no staffing restrictions were applied. In SA3 we assumed cases started within 30 min after admission. Since time is required to transport the patient to the OR, SA3 closely approaches that assumption. Comparing results from SA3 with results from the basic scenarios showed that not accounting for safety intervals led to a higher demand for staff in order to maintain low percentages of patients not treated immediately. Hence, adopting safety intervals, as is done in this study, lowers staffing levels beyond those determined by methods such as described by Tucker et al. (6). SA4 and SA5 show that extending safety intervals beyond
what is medically reasonable leads to a further reduction of required staff. The same results also show that hospitals that have a similar case mix volume, but with a different composition from Erasmus MC's case mix, may have different staffing levels. We recommend that all hospitals determine appropriate safety intervals before deciding upon the required staff for night shifts. We also recommended that hospitals not rely solely on anesthesia billing records, since the latter do not account for safety intervals. Similarly, hospitals should not reduce staffing and extend waiting intervals without accounting for safety, as has been noted for some hospitals (20).

SA6 showed that recovery room occupancy at $23: 00 \mathrm{~h}$ has some effect on the outcome, although the percentages of patients who would need to wait longer than 30 min remained within safe margins. Hence, decision-making in Erasmus MC was not affected by this modeling assumption. Nevertheless, hospitals that do have a substantial number of patients in the recovery room at 23:00 h should incorporate this in their modeling.

Several studies have shown that safety intervals or medical triage systems for emergency patients are hard to establish $(4,21)$. In this study, we used safety intervals determined by surgeons of Erasmus MC. We do not claim that these intervals are valid in general. However, establishing safety intervals facilitates medical decision-making on emergency patients.

A significant fraction of the cases performed during the night shift can be postponed to the day shift (22-24). Safety intervals help to identify cases that cannot be postponed. In future research, we will investigate the performance of a model with more precisely measured safety intervals. This would allow modeling the benefits of early treatment in terms of mortality and risks of complications for certain patient categories.

In the model we assumed transport or travel times between the OR and the ICU or the wards to be 30 min . Shortening of these times is likely to improve the performance in all scenarios, which in the end allows for a further reduction of number of nurses required to be on call in the OR during the night.

In conclusion, this study shows that a discrete simulation model is useful in determining optimal size and composition of an emergency team, considering patient safety. Its flexibility provides for different input variables, such as safety interval frequencies, which might affect the outcome measures. Moreover, the approach allows evaluating different scenarios as a means to support complex managerial decision-making. Any hospital that reconsiders its staffing during night shifts should carefully consider the safety intervals of its patient mix. Using safety intervals, this model showed that at the test medical center it was possible to deploy fewer surgery and anesthesia nurses on call during the night without diminishing the quality of care.

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## Chapter 10

## Concluding remarks and implications

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## Chapter 10

## Concluding remarks and implications

This thesis describes mathematical models and managerial prerequisites for application to surgical patient planning. We presented an approach for cyclic and integrated operating room planning, called master surgical scheduling, and models for efficient planning of emergency surgical cases. The basic idea of master surgical scheduling is to cyclically execute a master schedule of surgical case types to optimize at the same time operating room utilization and to provide steady and thus more predictable patient flows in hospitals. The approach is generic as it can be used in conjunction with other elective surgical patient planning strategies and while it can be adjusted to characteristics of individual hospitals.

## Dealing with the stochastic nature of hospital processes

Processes in hospitals are characterized by their stochastic nature, eventually resulting in many last minute changes to deal with. The approach chosen in this thesis explicitly creates room to deal with such changes. Take for instance the planning of required operating room capacity for emergency surgical patients during day and night times. Models in this thesis demonstrate the effect of reserving capacity on patient measures and efficiency and are therefore useful to assist decision-making of hospital management. Sufficient room for last-minute changes is an important prerequisite for logistical models to be successfully implemented in hospitals. Another prerequisite is that the actual scheduling of individual patients remains the responsibility of medical specialists. Both prerequisites are satisfactorily covered in the master surgical scheduling approach.

## Integrating hospital departments

A hospital typically comprises of several departments that function often independently. Patients may visit different departments within a single clinical pathway. Hence, planning and variability of work volume at one department can have large impact on another. Timely and effective information sharing is essential to be able to deal with such variability. However, in practice this is hard to organize on a daily basis, which results in little insight in upcoming patient volumes. This causes departments either to overestimate their future demand which results in low utilization or underestimate demand which results in high work pressure and / or cancellations. The proposed master surgical scheduling approach creates stability in resource usage patterns without the need to organize information sharing on a daily basis. Hence, it supports the efficient use of expensive and scarce hospital staff and resources.

## Cyclic and integrated planning in a broader scope

Cyclic and integrated planning of patients and creating sufficient capacity to deal efficiently and medically soundly with emergency surgical patients can be modified and
applied to other patient flows in hospitals. Consequently, the 7 -stepwise plan for implementation of master surgical scheduling (Chapter 1) is to be used in a more generic way. Namely, identify the scope of the logistical problem, gather data, plan capacity of involved resources, define patient groups, construct a cyclic basic schedule that integrates multiple resources based upon the patient groups, use the basic schedule, and update periodically the previous steps is a systematic way of dealing with logistical problems that involve multiple resources, multiple patient groups and various decision-makers. This thesis presented an application of this generic approach to surgical patient planning.

## Using Operations Research models in practice

Operations research models are more easily applicable in practice if they account for the previously mentioned factors, autonomy and room for last minute changes, and if they keep model complexity low. For instance, the number of input and output parameters and variables need to be reasonably small and more advanced mathematical techniques such as used in this thesis need to be hidden for end-users. Keeping the number of input and output parameters small enhance the easy explanation of the model to end-users. Important for hospital logistics is to provide insights in trade-offs between different objectives to decision-makers. In this way the complex and variable nature of hospital logistics is structured, which enhances problem-solving, and provision of solutions in an understandable manner.

## Implications for practice

This thesis presents tools to improve operating room planning in such a way that it is integrated with processes of other hospital departments, while surgeons' autonomy and treatment of emergency patients is sufficiently ensured. A next step is to actually use the techniques in hospitals of which an example is presented in Chapter 6. Whether or not the mathematical models deliver results to their full potential depends on the actual implementation in hospitals. The strengths and weaknesses of the models should be carefully explained to physicians, nurses and other hospital staff. Implementation of a new logistical approach only delivers desired results if people actually change their 'old' behavior. In addition to change-management it is necessary that managers and other decision-makers at operational and tactical level in a hospital organization are aware of the need for logistical improvements. When logistical improvement is not demanded from strategic level or tactical incentives for changes in the logistical process changes are missing, a hospital organization will not improve its processes and hence its effectiveness and efficiency.

## Need for reliable information

Strategic problems typically consider long term investments and structural organizational changes. Creating awareness for improving efficiency is from an operations research perspective in general done by performing quantitative analysis on hospital
processes. Ideally, after creating incentives and awareness by evidenced-based quantitative analysis, lower hierarchical decision-makers should request for assistance for improving patient planning and scheduling. For the previously mentioned analyses as well as for the 7 -steps master surgical scheduling approach reliable and available information is essential.

## First steps

Strategic decision-makers should take the lead to create incentives by using clear, objective, and evidenced-based arguments for their decisions, while asking departments and their employees to do the same. However, professionals in a hospital may be unfamiliar with more advanced logistical tools and models. Therefore, a hospital should ensure that logistical tools and knowledge come available. For this, hospitals should hire at strategic level advisors that have a high-level knowledge of the fields of operations research and operations management in health services. These advisors should give advice at strategic logistical problems and assist strategic-decision makers to create awareness and incentives at lower hierarchical levels for improving efficiency.

## Summarizing

Operations research has a long history in improving logistics. In this thesis mathematical models were presented that are readily available to be applied for efficient patient planning in hospitals. Moreover, we have discussed that hospitals can benefit from operations research models when these get a permanent place in hospital organizations. Application of mathematical models requires careful modeling and problem solving to provide sensible and easy-to-understand models as well as creating awareness and incentives in hospital organizations to actually implement logistical models. Cooperation between operations researchers, physicians and other decision-makers is therefore essential to improve hospital efficiency.

## Nederlandse samenvatting (Summary in Dutch)

Dit proefschrift beschrijft mathematische modellen en organisatorische randvoorwaarden voor implementatie hiervan voor patiëntplanning in ziekenhuizen. Deze worden toegespitst op een cyclische en geïntegreerde wijze van het plannen van chirurgische patienten master surgical scheduling - inclusief modellen voor het efficiënt plannen van spoedoperaties. Het idee achter master surgical scheduling is het cyclisch uitvoeren van een basisrooster van operatietypen zodanig dat het optimaliseren van operatiekamerbenutting gelijktijdig gebeurd met het spreiden van bedbezetting op klinieken en intensive care. De opzet is generiek zodat tijdens de uitwerking rekening gehouden kan worden met ziekenhuisspecifieke karakteristieken. Typerend voor master surgical scheduling en de modellen voor de planning van spoedpatiënten is dat de uiteindelijke roostering van patiënten onder de eindverantwoordelijkheid blijft van medisch specialisten. Daarmee wordt aan een belangrijke voorwaarde voor toepassing in ziekenhuizen voldaan: de medische autonomie van specialisten blijft gewaarborgd.

In Hoofdstuk 1 worden de voorwaarden beschreven voor een succesvolle implementatie van planning- en roosterbenaderingen in ziekenhuizen. Bovendien worden de voor- en nadelen van gecentraliseerde en gedecentraliseerde planningsbenaderingen vergeleken. Met gebruik van beschikbare literatuur op het gebied van operatiekamerplanning en roostertechnieken werken we vervolgens het concept van master surgical scheduling uit en plaatsen dit ten opzichte van eerder genoemde voor- en nadelen van planningsbenaderingen. Om master surgical scheduling te introduceren wordt een zevenstappenplan uitgewerkt. De uiteindelijke toepassing van de geïntroduceerde benadering hangt af van de omvang en organisatie van een ziekenhuis. Aan de hand van Operations Management literatuur worden potentiële problemen bij implementatie van master surgical scheduling in de praktijk besproken. We concluderen daarbij dat de verschillende vormen van ziekenhuisorganisatie zeker invloed hebben op de toepassing, maar dat het concept van master surgical scheduling voldoende flexibel is om toegepast te worden in elk van de bekende verschijningsvormen van ziekenhuisorganisaties.

Hoofdstuk 2 beschrijft een methode om de kosten van organisatorische beperkingen in operatiekamercomplexen te berekenen. Deze beperkingen hebben betrekking op de weigering van snijdende specialismen om operatiekamercapaciteit te delen. We maken deze kosten objectief inzichtelijk door toepassing van mathematisch programmeringtechnieken. Een ziekenhuis kan gebaseerd op dergelijke berekeningen beslissen om dergelijke organisatorische beperkingen op te heffen. Deze beslissingen hebben direct invloed op de condities waaronder een master surgical scheduling benadering in een ziekenhuis wordt uitgewerkt.

Hoofdstuk 3 ontwerpt een methode om standaard operatietypen te klassificeren. Deze operatietypen fungeren als bouwstenen om een basisrooster voor operatiekamers op te stellen. Ons doel is deze operatietypen te klassificeren zodanig dat de typen medisch en logistiek homogeen zijn. Hiervoor gebruiken we een gemodificeerde versie van de Ward's
hierarchical cluster method. Deze techniek is succesvol getest op basis van een casus van een regionaal ziekenhuis.

Hoofdstuk 4 beschouwt de constructie van de daadwerkelijke basisroosters. Dit complexe mathematische probleem bestaat uit het roosteren van operatietypen, welke samengesteld kunnen worden met de techniek uit Hoofdstuk 4, zodanig dat de operatiekamerbenutting gemaximaliseerd is en de bedbezetting van klinieken gelijkmatig verspreid is. Hier stellen we een tweefasenaanpak voor. In de eerste fase worden operatiekamerdagroosters gemaakt door een kolomgeneratie heuristiek. Deze operatiekamerdagroosters geven een set van operatietypen aan die gezamenlijk in een operatiekamer op één dag uitgevoerd kunnen worden. In de tweede fase worden de operatiekamerdagroosters met behulp van een integer lineair programmeringmodel in een planningscyclus gepland, zodanig dat de bedbezetting gelijkmatig over de planningscyclus verspreid is. Rekenkundige experimenten laten zien dat de tweefasenaanpak goed uitwerkt voor zowel de operatiekamerbenutting als voor een goed gespreide bedbezetting.

Hoofdstuk 5 evalueert het potentiële effect van het gebruik van een master surgical schedule in een groot academisch en in een groot regionaal ziekenhuis op basis van verbeterde operatiekamerbenutting en gespreide bedbezetting. Berekeningen tonen aan dat winst behaald wordt in beide ziekenhuizen. Wel is de winst in het regionale ziekenhuis groter dan in het academische ziekenhuis. Daarnaast bediscussiëren we in dit hoofdstuk de organisatorische voordelen van het gebruik van een master surgical scheduling benadering ten opzichte van andere planningsbenaderingen in ziekenhuizen.

Hoofdstuk 6 beschrijft de ingebruikname van de master surgical scheduling benadering in het Beatrix ziekenhuis (Gorinchem, Nederland). Hierbij gaan we nader in op de moeilijkheden bij het implementatietraject dat is uitgevoerd op basis van de in Hoofdstuk 2 beschreven stappen. Hoewel er momenteel nog geen complete kwantitatieve post- implementatie analyse kan worden uitgevoerd, meldt het ziekenhuis grote logistieke en organisatorische verbeteringen.

Hoofdstuk 7 analyseert de toepassing van een full-service concept binnen een operatiekamerafdeling. Een dergelijk concept garandeert dat patienten worden geopereerd op de vooraf geplande datum. Deze garantie is alleen toepasbaar indien operatieroosters voldoen aan vooraf opgestelde eissen. Met behulp van discrete-event simulation analyseren we de effecten op benutting, uitloop en aantal afgezegde operaties als het full-service concept op verschillende manieren wordt toegepast.

Hoofdstuk 8 onderzoekt de efficiëntie van het gebruik van een speciale spoedoperatiekamer. Onze analyse toont aan dat voor een groot academisch ziekenhuis het gebruik van een spoedoperatiekamer in plaats van spoedtijd op electieve operatiekamers niet alleen inefficiënt is, maar dat dit ook zorgt voor langere wachttijden voor spoedpatiënten. Een verklaring hiervoor is de sterk toegenomen planningsflexibiliteit
binnen operatiekamercomplexen waar spoed in alle kamers kan worden gepland ten opzichte van complexen die een speciale spoedoperatiekamer gebruiken.

Hoofdstuk 9 bepaalt de optimale inzet van operatiekamerpersoneel tijdens de nacht die in het ziekenhuis aanwezig en op oproepbaar zijn. Bij bepaling hiervan modelleren we expliciet zogenaamde safety intervals voor spoedpatiënten. Deze safety intervals geven een periode aan waarbinnen een spoedpatiënt geopereerd kan worden zonder verhoogde morbiditeit of verlaagde kans op volledig herstel. We tonen met behulp van discrete-event simulatie en safety intervals aan dat de hoeveelheid ingezet personeel ten opzichte van andere methoden verminderd kan worden.

Hoofdstuk 10 geeft een samenvatting van de verschillende instrumenten om de patiëntplanning te optimaliseren. Het toepassen van deze instrumenten zorgt voor het gelijktijdig optimaliseren van operatiekamerbenutting, klinieken en intensive care units. Bovendien zorgt het repetatief uitvoeren van een master surgical schedule voor een stabiele en daardoor voorspelbare instroom van patiënten op klinieken. Voorwaarden voor het succesvol imlementeren van logistieke modellen in ziekenhuizen zijn de ruimte voor last-minute veranderingen en de eindverantwoordelijkheid van medisch specialisten over de patiëntroostering. Aan beide randvoorwaarden voldoet het concept master surgical scheduling.

## Curriculum Vitae

Jeroen van Oostrum was born in 1980, in Maarssen, The Netherlands. After finishing his secondary education (Athenaeum) at St.-Gregorius College in Utrecht, he went to the University of Twente in 1999. He graduated in 2005 for his master's Applied Mathematics, with as specialization Discrete Mathematics and Mathematical Programming. During his studies he took a minor course (8 months) in "Sustainable development in a North-South perspective" including a 5 months stay at Abraham Academy in Rosterman, Kenya. He performed an internship in London, UK, at Cass Business School (City University) resulting in an accepted academic paper in Annals of Operations Research. From December 2004 to October 2005 Jeroen worked on his final thesis in a joint project of Erasmus University Medical Center and University of Twente on operating room planning and scheduling.

From September 2005 onwards he worked as an academic researcher and business consultant for the Erasmus University Medical Center. Project topics comprise, amongst other, bed planning, operating room capacity planning and patient scheduling. In September 2007 Jeroen accepted a position as PhD candidate on a research project jointly proposed by the Econometric Institute (Erasmus School of Economics, Erasmus University Rotterdam) and the Department of Operating Rooms (Erasmus University Medical Center). Under supervision of prof.dr. Albert Wagelmans and dr. Geert Kazemier he completed his PhD thesis. From January 2009 onwards he works as manager Business Intelligence Center at Erasmus University Medical Center.

Jeroen is married to Linda. He is a second degree black belt karate and instructor within the organization Shotokan Karate of America (SKA).

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## APPLYING MATHEMATICAL MODELS TO SURGICAL PATIENT PLANNING

On a daily basis surgeons, nurses, and managers face cancellation of surgery, peak demands on wards, and overtime in operating rooms. Moreover, the lack of an integral planning approach for operating rooms, wards, and intensive care units causes low resource utilization and makes patient flows unpredictable. An ageing population and advances in medicine are putting the available healthcare budget under great pressure. Under these circumstances, hospitals are seeking innovative ways of providing optimal quality at the lowest costs.

This thesis provides hospitals with instruments for optimizing surgical patient planning. We describe a cyclic and integrated operating room planning approach, called master surgical scheduling, and models for efficient planning of emergency operations. Application of these instruments enables the simultaneous optimization of the utilization of operating rooms, ward and intensive care units. Moreover, iteratively executing a master schedule of surgical case types provides steady and thus more predictable patient flows in hospitals.

The approach is generic and so can be implemented taking account of specific characteristics of individual hospitals. Prerequisites for successful implementation of logistical models in hospitals comprise sufficient room for last-minute changes as well as keeping the ultimate responsibility for individual patient scheduling with medical specialists. Both are satisfied in the master surgical scheduling approach which has already been successfully implemented in hospitals.

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