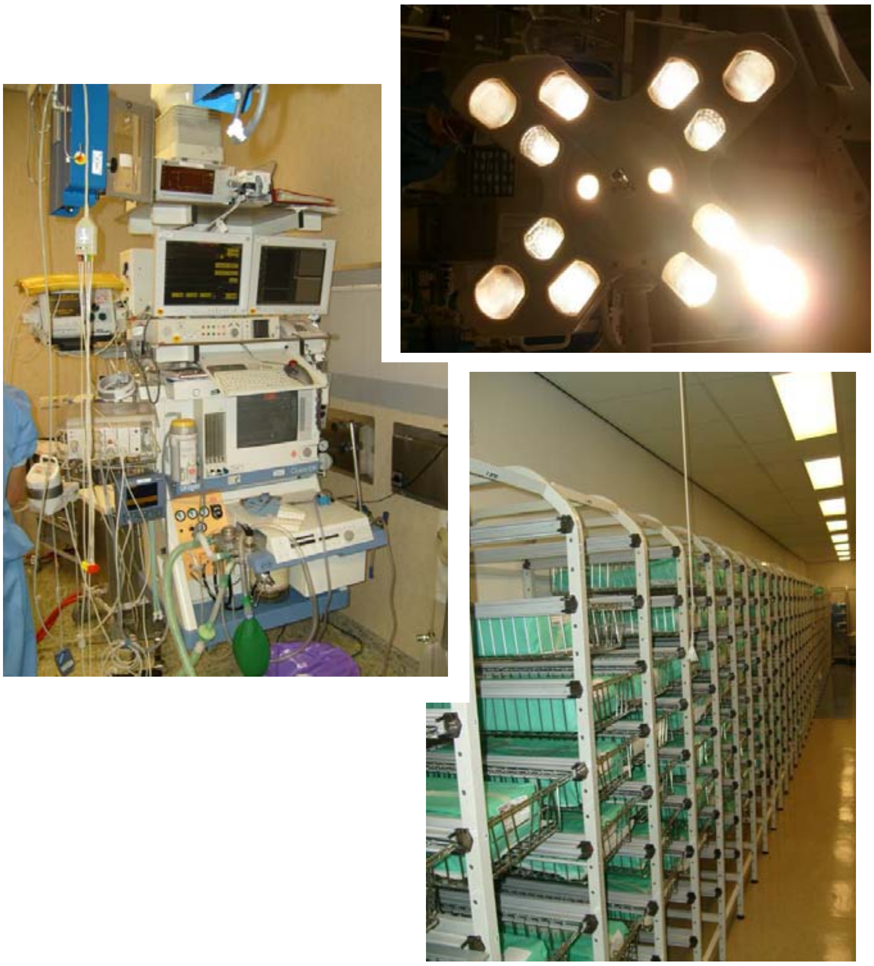
Surgery Scheduling with Limited Physical Resources



Master's thesis

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Isala klinieken

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Voorwoord

Na zeven jaren studeren is het zover: Dennis wordt burger. De studiecombinatie van Technische Natuurkunde met Technische Bedrijfskunde is misschien niet de meest voor de hand liggende, maar voor mij wel één die prima bevallen is! De techniek en wiskunde op een begrijpelijke manier in de praktijk brengen heb ik altijd een mooie uitdaging gevonden. Voor mijn afstudeeropdracht wilde ik dan ook graag in een ziekenhuis aan de slag, omdat dit nog een andere invalshoek oplevert: de zorg.

De inhoud van mijn onderzoek staat beschreven in dit verslag. Een onderzoek en verslag waar ik behoorlijk trots op ben! Hard werken, veel meemaken en leren. Natuurlijk heb ik bij het neerzetten van dit resultaat veel hulp gehad van de mensen om mij heen. Deze mensen wil ik nu graag even bedanken.

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Dennis Buitelaar

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Abstract

Limited availability of physical resources at the Operating Room (OR) department results in waiting times between surgeries. We develop elective surgery scheduling algorithms to increase efficiency of the OR department by reducing the waiting time.

The two most influential performance indicators that the management of the OR department uses, are utilization and the amount of overtime in the ORs. The objective is to increase utilization and to decrease the amount of overtime. We propose multiple algorithms to schedule surgeries that require a physical resource, either as early as possible, or clustered together as much as possible.

We demonstrate that our approach reduces the amount of waiting time between surgeries, increasing efficiency of the OR department. This outcome results from computational experiments performed in collaboration with Isala klinieken Zwolle, the largest non-academic hospital in the Netherlands. This hospital provided us with historical data.

1 Introduction

This research was initiated by the management of the Operation Room and Intensive Care department (OR/IC) of the hospital Isala klinieken Zwolle. OR/IC management is confronted with the problem of a low efficiency of their OR departments causing high expenditure in terms of employee salary, material costs and vacancy costs. In today’s setting of a new social health care system, ageing society, long waiting lists and increasing competition between healthcare institutions [Hans, 2007], efficiency becomes more and more important. In this research we focus on the operating department of location Sophia to find ways to improve this efficiency.

In 1998, Isala klinieken was formed by the merger of two hospitals: the hospital “Sophia” (SZ) and the hospital “De Weezenlanden” (WL). Isala klinieken is the largest, non-academic hospital in the Netherlands with 5,900 employees and 1,000 beds. Each year, Isala klinieken attends to more than 475,000 outpatient visits and almost 40,000 admissions. Besides the base care the hospital provides, Isala klinieken is also a top clinical hospital and an educational hospital [Isala, 2007]. Isala klinieken and the individual departments are constantly looking for ways to improve their efficiency to be able to deliver top quality cure and care, at an acceptable price.

Availability of personnel and material resources is one of the many constraints the surgery schedule has to comply with. At location SZ, the main difficulty in creating a surgery schedule is the availability of resources. To investigate the effect new methods of surgery scheduling have on the efficiency of the OR department, we develop scheduling algorithms that create surgery schedules specifically optimized to the availability of the most critical of the physical resources: the X-ray machine.

Unexpected events such as the arrival of emergency patients and surgeries that take longer than expected lead to delays and, as a consequence, personnel has to wait for resources to become available. The goal of this research is to increase efficiency of the OR department Therefore, we define the following problem statement:

“How can the OR department’s efficiency be improved?”

To find ways to improve the OR department’s efficiency, we pose the following research questions:

1. *How does the management of the OR department define and measure efficiency?*
2. *What is the OR department’s efficiency at this moment?*
3. *How are the planning processes at the OR department currently organized?*
4. *How can we efficiently schedule surgeries and surgery resources?*
    a. *What are the possibilities to adjust the surgery schedule?*
    b. *What are the constraints the surgery schedule has to comply with?*
5. *What are the effects of implementing the new ways of scheduling surgeries?*

To determine how management of the OR department defines and measures efficiency, we give corresponding results answering question (1) in the first part of Section 2.2.1. To compare the results of our research with the actual performance indicators, we determine the current levels of performance of the OR department. Investigations to question (2) are presented in the last part of Section 2.2.1. Furthermore, we need to determine how we can influence the performance indicators. The answer to research sub question (3) we give in Section 2.2.2 leads us to focus the research on planning and scheduling of surgeries and resources at the operational offline level. We focus on this level in research sub question (4). We determine the possibilities of the surgery planner to change the surgery schedule and describe these possibilities in Section 2.2.3. We also determine the constraints the surgery schedule has to comply with. We describe these constraints in Section 2.2.4. In Section 3.1 we restate the processes, possibilities and constraints we take into account in this research, leading to a formal problem description in Section 3.2. Section 4 describes various solution approaches. To test the performance of these solution approaches, we perform discrete event simulations. Section 5 presents the results of these simulations. Section 6 gives the conclusions based on the results of the simulations and reflections on the results.

2 Context and position of this research in the literature

In this section we describe the context of our research at Isala klinieken, and the position this research takes in the relevant literature. Hans, Van Houdenhoven, and Wullink (2006) propose a hospital planning and control framework. The framework consists of four managerial areas and four hierarchical levels. Figure 1 gives a graphical representation of this framework and its application to a hospital.

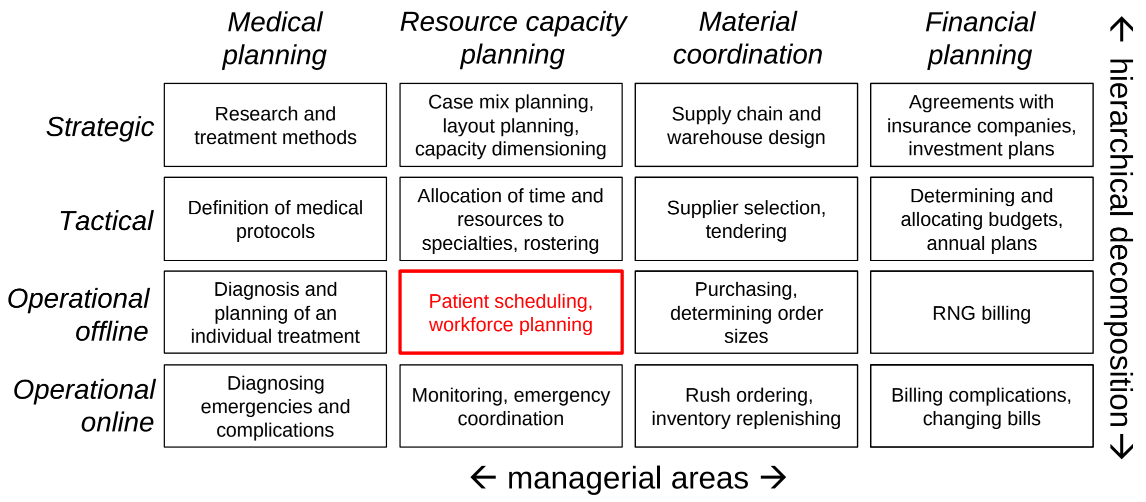

Figure 1: Framework for Hospital Planning and Control [Hans *et al.*, 2006]

At Isala klinieken, the same levels and areas are distinguished. Therefore, we describe the context of this research in terms of this framework. To clarify the position of this research in the framework, we briefly describe all hierarchical management levels proposed by [Hans *et al.*, 2006] in Section 2.1. For each level, we give a short description of the four managerial *areas*. The descriptions of the four levels at Isala klinieken have been written in collaboration with hospital employees (e.g. surgery planners and OR management). From this collaboration, it became clear the surgical schedule has to comply with a large number of resource constraints: at least 35 have been identified by the surgery planners. As the surgery schedule has to comply with this large number of constraints, creating a surgery schedule poses a complex challenge. Therefore, we focus our research on Resource Capacity Planning at the Operational Offline level. Figure 1 highlights this level in red. We describe this level in more detail in Section 2.2.

2.1 Management levels

The framework proposed by [Hans *et al.*, 2006] describes the interaction between four levels of control within the hospital. To position our research in the framework, we briefly describe the four hierarchical levels in this section. To clarify the position of the OR department within the hospital, the OR department is highlighted in red in the organizational chart of the hospital in Figure 2.

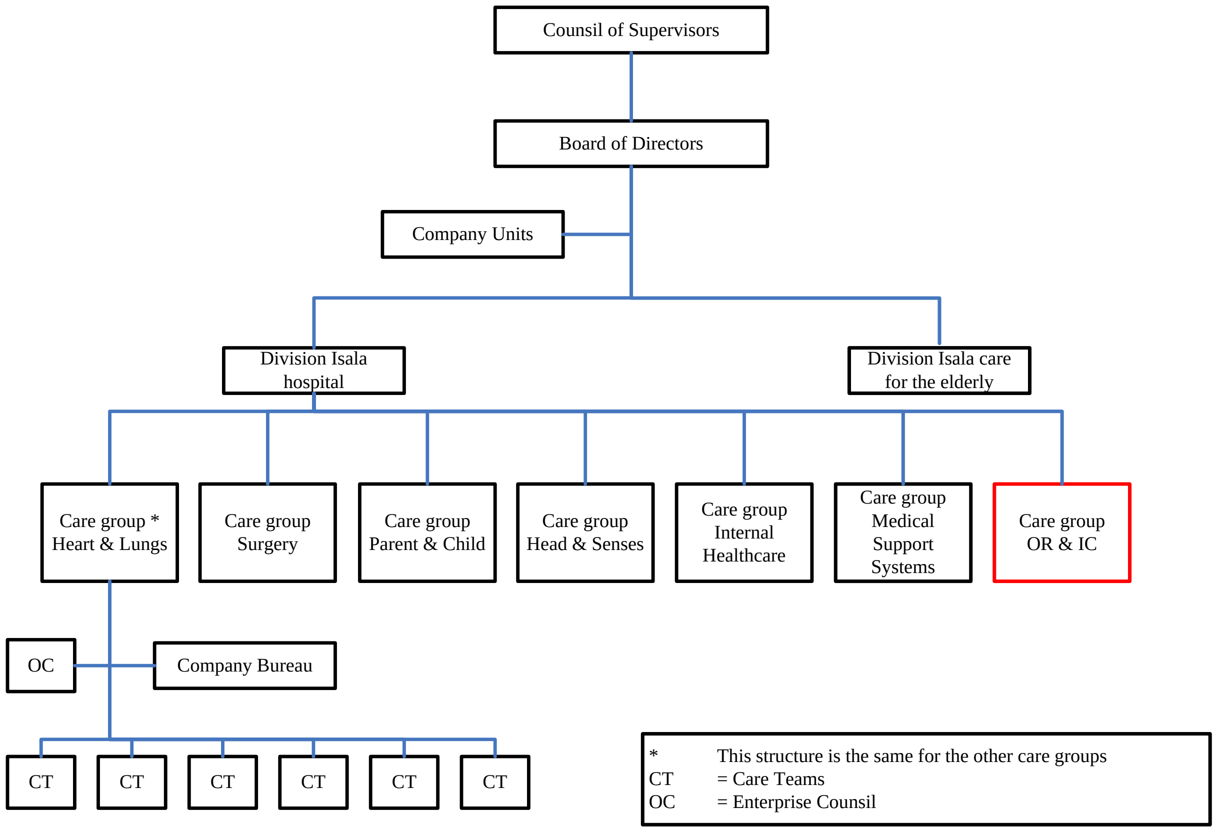

Figure 2: Organizational chart of Isala klinieken, Zwolle [Isala, 2007]

We describe the highest level, strategic planning, in Section 2.1.1. The next level translates the mission determined at the strategic level into medium-term objectives. We describe this level in Section 2.1.2. The third level is the operational offline level. This level creates detailed plans and schedules to control day-to-day activities. We describe this level in Section 2.1.3. The fourth level is the operational online level. This level monitors and reacts to disturbances to the offline schedule. We describe this level in Section 2.1.4.

2.1.1 Strategic management level

The highest managerial level aims at the hospital's long term goals. At this level, the mission of the hospital is determined. At Isala klinieken, managers at the strategic level decide about:

- Medical planning: e.g. the decision to educate and train medical students at Isala klinieken.
- Resource capacity planning: capacity dimensioning. For example the patient mix at Isala klinieken is a strategic decision: a large number of relatively standard procedures, in combination with complicated, non-standard, top clinical procedures. This means surgical procedures performed at the hospital differ largely in terms of

surgery duration and surgery duration variability. For example Kerkkamp (2006) suggests splitting up different patient-flows throughout the hospital can improve the hospital performance.

- Material coordination (e.g. decisions on whether or not to outsource ICT)

- Financial planning (e.g. agreements with insurance companies and investing in a new building)

2.1.2 Tactical management level

The tactical management level defines medium-term objectives, based on the decisions made at the strategic level. Examples of decisions taken at this level at the managerial areas defined by [Hans *et al.*, 2006] are:

- Medical planning: determining protocols for the process before the surgery can take place.

- Resource capacity planning: capacity allocation. The time available at the OR department to perform surgeries is assigned to the surgical specialties according to the "closed block" method described by [Hans, 2007]. This results in a "Room Opening Plan" (ROP). The ROP is a weekly schedule that defines per OR on a daily basis, the specialty that is scheduled to perform surgeries in that OR. We present the ROP for location SZ of Isala klinieken in Section 5.1.

- Material coordination: selecting a supplier for medical equipment.

- Financial planning: determining and allocating budgets to departments within the hospital.

2.1.3 Operational offline management level

Managers at the operational offline level create detailed plans and schedules for resources and materials for a time horizon of typically 1 to 2 weeks. The adjective "offline" means the plans and schedules are created before actually executing them. Examples of activities at this level in the 4 managerial areas of [Hans, 2006] are:

- Medical planning: diagnosing a broken leg and planning of an orthopedic surgery.
- Resource capacity planning: capacity assignment. Assign material and personnel resources (e.g. IC beds, surgery assistants and X-ray machines) needed to perform surgeries. Research by [Hans, 2006] suggests the performance at the OR department can be improved by taking the portfolio effect into account during the creation of a surgery schedule at the operational offline level. This means scheduling surgeries with highly variable surgery durations together in one OR as well as scheduling surgeries with less variable surgery durations together.
- Material coordination: purchasing prostheses for orthopedic surgeries.
- Financial planning: billing the costs of an X-ray used during an orthopedic surgery.

This research focuses on resource capacity planning in particular at the operational offline level. In Section 2.2 we describe for this level the planning process, the constraints on the surgery schedule, the possibilities to change the schedule, the current performance of the OR, and the way information regarding patients and surgeries is handled.

2.1.4 Operational online management level

This level deals with monitoring and reacting to unforeseen or unanticipated events. This means that during the execution of the plans and schedules created in the operational offline phase, disturbances such as emergency surgeries can occur. The 4 managerial areas of [Hans, 2006] at this level deal with:

- Medical planning: diagnosing an emergency patient that has just arrived at the hospital.
- Resource capacity planning: monitoring and changing the surgery schedule because an emergency patient has to be operated immediately.
- Material coordination: rush ordering of cleaned materials at the Central Sterilization Department (CSD).
- Financial planning: changing the bill for a surgery if complications arise during surgery.

Summary of the Management levels

In the previous subsections we discussed management in the hospital at four different levels of control. The highest level describes the hospital at the strategic level. The second level describes the decisions that influence the OR department at a tactical level. The third level describes the way plans and schedules are created for the OR department at an operational offline level. At the fourth level the plans and schedules created at the Offline level are monitored and adjusted during execution.

2.2 Resource capacity planning at the operational offline level

Creating a surgery schedule at the operational offline level is complex due to the many constraints the surgery schedule has to comply with. In this section, we therefore describe the current surgery planning processes, the constraints that apply to the surgery schedule, the possibilities to change the surgery schedule, the current performance of the OR and the way information regarding patients and surgeries is currently handled. This information is used in Section 3 and 4 to respectively formulate a formal problem description and to propose algorithms to create surgery schedules.

To allow us to compare the performance of the proposed algorithms, we describe the current performance of the OR in Section 2.2.1. To determine what we can change to improve the performance of the OR department, we describe the constraints the surgery schedule has to comply and the possibilities to change the surgery schedule in respectively Section 2.2.2 and 2.2.3. We describe the surgery planning process in Section 2.2.4 and the way information regarding patients and surgeries is handled in Section 2.2.5.

2.2.1 Performance

The performance of the OR department is measured by performance criteria such as the utilization of the ORs, and the amount of overtime. As we want to compare the performance of the algorithms we propose in Section 4, we first describe how the performance of the OR department is measured. Second, we describe how performance is influenced by changing the surgery schedule.

Performance measurement

Management of the OR department uses three performance indicators: utilization of the operating rooms, amount of overtime, and the number of cancelled elective surgeries. In the following the former two indicators are specified formally:

$[B, E]$	: time interval each OR is opened
$T_s(k)$	: the start time of surgery k
$T_c(k)$	: the completion time of surgery k
K	: set of all elective surgeries in a year
$T_e = \sum_{k \in K} \left(\min\{T_c(k), E\} - T_s(k) \right)$	: the total actual duration of all surgeries in a year, where overtime is not counted
$h = E - B$	: total regular time per day the OR department is opened
D	: set of days in a week the OR department is carrying out elective surgeries
J	: set of ORs available
w	: number of weeks in a year the OR department is opened
$T_a = h * \lvert J \rvert * \lvert D \rvert * w$	: the total time available in a year to perform surgeries in
$U = \frac{T_e}{T_a}$	: utilization of the operating rooms
O_{dj}	: overtime on day d in OR j
$\sum_{d \in D} \sum_{j \in J} O_{dj}$	: total amount of overtime in a year

The total actual duration of all surgeries in a year is calculated by calculating the difference between the completion time and the start time of each surgery performed and adding these individual durations. However, if the completion time of a surgery is outside regular opening hours of the OR department, the completion time of the surgery is set to E for the calculation of the utilization U. This means that the part of the surgery that is performed outside regular opening hours is not taken into account as surgery time. Changeover times between surgeries are also not taken into account as surgery time. This also means that $U > 1$ can never occur in practice. The maximum value for U therefore depends on the number of changes that occur between surgeries. Each time a changeover occurs, the OR is unavailable for surgeries, and so U decreases. Overtime occurs when surgeries finish after the planned closing hour E for the ORs. Reasons that overtime occurs may be that surgeries take longer than expected or emergency surgeries arrive. If at some point of the day it is expected that a next surgery may lead to overtime, it may be decided to cancel the surgery. This decision to cancel a surgery is left to the surgery planner and medical personnel.

Influence of the schedule on the performance

The two performance indicators valued most by the management of the OR department are utilization and overtime. Optimizing both utilization and overtime however leads to a trade-off. For example, optimizing the surgery schedule just to maximize the utilization leads to completely filling the OR day with surgeries and planning surgeries in overtime to make sure the OR performs as many surgeries as possible on a day, thus maximizing the utilization and at the same time creating a surgery schedule that leads to a large amount of overtime. Minimizing the amount of overtime and maximizing the utilization are opposing goals: increasing the utilization by scheduling more surgeries increases the risk on overtime, and decreasing the risk on overtime by scheduling fewer surgeries will decrease the utilization. As it adds to the risk of overtime and cancelled surgeries, scheduling surgeries in overtime is not allowed. We explain the current practice of creating the surgery schedule in more detail in Section 2.2.2.

2.2.2 Planning processes

In this section we describe the process of creating a surgery schedule. This process start at the moment a specialist decides a patient needs surgery, and stops at the moment the surgery finishes.

When a specialist decides a patient needs surgery, the outpatient clinic of the specialty this specialist belongs to puts this patient on a surgery list. The administration department of this specialty has to make a provisional surgery schedule based on this list; this means creating a surgery schedule with the information locally available at the administration department of the specialty. Hereby the following is taken into account: are all the urgent, unscheduled patients on the list, does the total expected duration of the surgeries on the list fit within the surgical time available to the specialty, and are the surgeons (of that specialty) available for the surgery. After making this provisional surgery schedule, the administration department sends it to the central planner of the OR department. When the central planner has obtained all the provisional schedules from the specialties, he performs further feasibility checks considering materials and personnel, time limits and constraints specific for a certain type of surgery such as the type of anesthetic that has to be used. If the surgery schedule complies with all constraints, the central planner approves this schedule. If one or more constraints are violated, he tries to change the schedule in such a way that the schedule becomes feasible. After the central planner has made the adjustments, he sends the schedule back to the specialties so the administration departments can inform the specialists and the patients. From that moment on, the schedule is final. Adjustments can now only be made due to unexpected circumstances such as emergency patients, patients that do not show up, or surgeries that are cancelled.

Summary of the processes

The administration departments of the specialties create a provisional surgery schedule and deliver this schedule to the central planner. The central planner then checks the schedule for feasibility together with the schedules of the other specialties. If necessary, the central planner changes the schedule until it complies with the constraints.

2.2.3 Possibilities of the planner

In order to create a feasible surgery schedule, the OR planner has multiple possibilities to adjust the schedule, e.g. a surgery can be scheduled in another OR, or the sequence of surgeries in an OR can be altered. The exact degrees of freedom available to the OR planner are discussed in this section

As described in Section 2.2.2, the surgery schedule is created in different phases. First, the central planner receives the schedules from the specialties and tries to create a complete, feasible schedule out of these partial schedules. In [Hans *et al.*, 2006] this phase is part of the operational offline scheduling. Changes made to the schedule during the offline phase do not affect the patients personally, as the patients are not yet informed about the day and time of their surgery. The next phase is described in [Hans *et al.*, 2006] as the operational online scheduling. Changes can also be made during execution of the schedule. The schedule is adjusted due to the arrival of emergency patients, surgeries that take less or more time than expected, and other unexpected circumstances. The patient knows the approximate time he is scheduled for surgery. Changes to the schedule made during this phase can therefore directly affect the patient. This occurs for example when a surgery takes longer than expected. Patients scheduled after this surgery potentially have to wait for their surgery to start.

There are three options to change the surgery schedule if it is not feasible:

1. Exchange surgeries within an OR-day. This option only changes the sequence of the surgeries that are performed in one OR on one day. It is mainly used to solve problems with availability of personnel and materials.

   Example:

   At location SZ, two X-ray machines are available to the OR department. In the current surgery schedule, three surgeries need an X-ray machine at the same time. In some cases this can be solved by changing the sequence in one or more ORs in such a way that the surgeries that need an X-ray machine are spread more evenly over the day. When this option is used during the online planning, it can have rather large effects on the patient's surgery experience. Suppose a surgery is scheduled at 9:00, but due to an exchange this surgery is delayed until 16:00, this will cause a lot of discomfort to the patient. Furthermore, as time progresses, fewer possibilities remain to exchange surgeries, as many of the surgeries have already been performed. At 9:00, surgeries during the whole day can be exchanged, but at 15:00, only a few surgeries still have to be performed. Hence, fewer possibilities remain to make changes. Therefore, the number of possibilities to resolve conflicts decreases as the day progresses.

2. Schedule the surgery in another OR. A surgery is moved to another OR, or two surgeries are exchanged across two ORs. This again can solve problems such as availability of personnel and materials if the surgery times change as well. Moreover it can solve problems involving the combination of two surgeries in ORs next to each other.

   Example:

   One anesthetist can handle two surgeries at a time in adjacent ORs. When a surgery is very intense, such as most child surgeries, an anesthetist can only assist at one surgery at a time. So if a very intense surgery is involved, another anesthetist has to handle the second

OR or the second OR has to remain empty during the intense surgery. Changing between ORs does not have a large effect on the patient's experience, if the scheduled surgery time does not change too much. If the start time of the procedure does change, it has the same effect on the patients experience as in the first option.

3. The third option is to cancel the surgery. If no other way can be found to make the schedule feasible, a surgery has to be cancelled. This is not the preferred way to solve a problem, as it creates many other problems. When a surgery is cancelled during the operational offline phase, the surgery has to be scheduled for another day and usually the administration department can schedule another surgery instead of the original one. When the surgery is cancelled during the operational on-line period the surgery also has to be scheduled for another day, and on top of that the patient has to be informed that his surgery will not take place that day. No matter what the reason for the cancellation is, the patient will dislike it.

One or more possibilities to change the schedule can also be combined. This occurs for example when two surgeries in one OR are exchanged as the surgery schedule does not comply with the constraint of X-ray machines. The schedule resulting from this exchange can contain a combination of surgeries in two ORs next to each other that are not acceptable to the anesthetist: Therefore, two surgeries can be exchanged between different ORs to comply with the wishes of the anesthetist.

Summary of the possibilities

We distinguish three possibilities to adjust the surgery schedule. First, the sequence of the surgeries that are performed within one OR on one day can be changed. Second, the surgeries can be exchanged across ORs. Third, a surgery can be removed from the schedule, i.e. cancelling the surgery. During operational offline planning, changes to the schedule and even cancelled surgeries will not be noticed by the patients, as the patients do not know yet when they are scheduled for surgery. The changes made during the operational online planning however directly influence the patient's experience in the hospital. Therefore, the number of changes to the schedule during this phase is kept to a minimum.

2.2.4 Constraints on the surgery schedule

The dependencies within the OR department and between the OR department and other departments lead to many constraints on the surgery schedule. We describe the following types of constraints: time, material, personnel, and the types of ORs available.

Time constraints

Time constraints have multiple causes and effects on the surgery schedule. First, we describe restrictions to the time available in an OR during one OR day. Second, we describe restrictions to the moment a surgery starts or completes.

Available time

The OR department opens every morning at 8:00 and the patient scheduled for the last surgery that day has to arrive at the recovery ward before 16:45. The expected duration of surgeries at Isala klinieken is based on the average surgery duration of the last 10 surgeries of that type performed, calculated per surgeon. The surgeries with the shortest and longest duration are left out, so effectively the average of 8 surgeries performed by the surgeon involved is calculated. The surgery planning system used at Isala klinieken, MCC, adds 10 minutes changeover time for each surgery. If the central planner deems it necessary, he will add another 15 minutes changeover time. This is done for example when very young children are involved. These patients need extra care during begin and end of the surgery. In terms of time constraints, a schedule is feasible as long as the total expected duration of the surgeries planned in any OR does not exceed the available time in that OR.

Start and completion time of surgical procedures

This type of constraint is mostly caused by connections between the OR and other departments of the hospital. For some surgeries, another department has to perform certain actions prior to the operation, or another department is needed after surgery. E.g. for oncology operations, the pathologist-anatomist (PA) is often needed directly after surgery to examine the tissue that has been removed. The tissue has to be delivered to the pathologist-anatomist before 16:30; otherwise he does not have enough time left that day to examine it. For the OR this means that this type of surgery cannot start after 14:30: it has to be scheduled earlier. Other examples include surgeries that require nuclear research, and surgeries performed on children that have to start as early in the morning as possible.

Resource constraints

Similar to the time constraints we described in the previous section, resource constraints have multiple causes and effects. To explain why we focus this research on X-ray machines, we first describe two types of resources. In Section 4 we propose a solution that specifically aims to tackle the "Oil Stain effect" for the X-ray machines. Therefore, we also give a brief description of the "Oil Stain effect".

Different types of surgery resources

Different types of resources are needed before, during and after the surgery. The first type of resource we describe includes for example an Intensive Care bed. This is usually reserved prior to surgery if the surgeon expects his patient to go to Intensive Care after this type of surgery. Therefore, the IC bed has to be ready before the patient comes out of surgery and the bed can be in use for days after the surgery. This means one surgery can influence the surgery schedule of the next day. The second type of resource we describe includes the X-ray machine. This machine is needed strictly during surgery, so this resource only has to be available from the moment the surgery starts until the moment it ends. We also assume that whether an X-ray machine is needed during surgery is known before the surgery starts. Therefore, while creating the surgery schedule, the surgeries that require an X-ray machine are known. Taking into account resources that can be in use before and after the surgery itself, makes the problem more complex as surgeries then can influence the surgery schedule on other days as well. Therefore, in this research we only take into account the type of resource that is in use only during the surgery (e.g. an X-ray machine).

Oil Stain effect

One specific difficulty with resources such as X-ray machines is that problems in one OR can lead to delays in other ORs.

Example:

An X-ray machine is in use during a surgery in OR 1. This surgery is expected to finish at 11:00. At 11:00, another surgery has to start in OR 1, and the X-ray machine is needed for a surgery in OR 2. During the surgery in OR 1 however, complications arise and these lead to a longer surgery duration. The surgery now finishes at 12:30. The delay of one surgery affects two other surgeries: the next surgery in OR 1 has to wait until the OR becomes available, and the surgery in OR 2 has to wait for the X-ray machine.

If a surgery that uses the X-ray machine takes longer than expected to finish, the effect of this can spread through the OR department like an oil stain. This is particularly difficult to cope with for the people who are waiting for the X-ray machine, but are unable to influence the surgery causing the delay. Therefore, we propose algorithms that aim to minimize the “Oil Stain effect” in Section 4.

Personnel Constraints

Personnel at the OR all have specific competences and authorizations. Therefore, each task has a limited number of people able and authorized to perform this task. This limits the possibilities of deploying personnel. Besides obvious limitations concerning medical personnel (e.g. surgeons and nurses) there are limitations to other types of personnel as well. For example, operating the X-ray machine requires personnel with a radiation certificate. During regular opening hours of the OR department, sufficient personnel to operate two X-ray machines is available. When surgeries that require an X-ray machine run late and have to be performed in overtime, this means personnel operating the X-ray machine have to work overtime as well. For each specialty, a percentage of the surgeries requires an X-ray machine. In Section 5.1 we discuss these percentages.

At location SZ, surgeries that require an X-ray machine are hard to schedule as there are only two X-ray machines available, and many surgeries performed at SZ require an X-ray machine. In some cases this problem can be easily solved by changing the sequence of the surgeries on one day such that no more than two sessions that require an X-ray machine are scheduled at the same time. When this is not possible, there are other possibilities to try and solve this problem. The planner can try to arrange for extra personnel to operate an X-ray machine. In some cases, the surgeon performing the surgery has the radiation certificate needed to operate the X-ray machine. In that case, the surgeon can take over the tasks of the radiation personnel. Taking this into account would increase the complexity of the problem. For our research, we assume a fixed capacity of the X-ray machines.

Usually, one anesthetist assists at two surgeries at the same time (two-room system). However, if the anesthetist indicates a surgery as very intense, the anesthetist has to be fully available for that surgery alone. This means that during this surgery, the anesthetist is not available for a second operating room and this room is unavailable for surgeries during that time. For example surgeries performed on children often require more attention from the anesthetist than surgeries performed on adults. Therefore, child surgeries are rather not scheduled in a room next to an emergency room as that would mean that during the child surgery, the emergency OR is unavailable for surgeries.

OR constraints

At the clinical OR department at location SZ, seven elective ORs and one emergency OR are available. Each specialty operating at SZ receives a fraction of the total elective OR time available, according to the “closed block” method [Hans, 2007]. The amount of time a specialty gets depends on the amount and length of the surgeries it expects to perform during the planning horizon. After the amount of OR time per specialty has been determined, it is divided over the seven elective ORs available. The seven elective ORs are largely identical and can be used interchangeably if needed. However, there are some differences (e.g. size, equipment) that make some ORs preferable to certain surgeries. For example an orthopedic surgery during which a hipbone is replaced is preferably done in a large OR, because of the large and heavy equipment needed during surgery. Such preferences are taken into account during the assignment of ORs to specialties to create a ROP. In case of emergency surgeries, the surgery planner can deviate from the ROP. This complicates the problem of scheduling surgeries. Therefore, we assume the ROP to be binding during our research. This means that all OR-days in the ROP are dedicated to one specialty. Surgeries of a specialty can only be performed during an OR-day of that specialty.

Handling of emergency patients

The two locations of Isala klinieken differ in the way emergency patients are handled. As most of the emergency surgeries are performed at location SZ, a dedicated emergency OR is available at this location. At location WL such a dedicated emergency OR is not available: emergency procedures are performed in the same ORs as elective surgeries. As this research focuses on location SZ, in this section we describe how the arrival of semi-urgent surgeries influences the elective surgery schedule. To describe the influence of emergency surgeries, we distinguish two types of emergency surgeries, i.e. emergency and semi-urgent surgeries.

Emergency surgeries have to be performed at the moment of arrival. For example a ruptured aorta has to be treated immediately because it is a life threatening condition. When an emergency surgery arrives, the impact on the elective surgery schedule of the day of the arrival is large as the emergency has precedence over all other surgeries scheduled that day and elective surgeries are postponed if resources needed for the surgery are used for the emergency surgery. However, this type of surgery is very rare. Therefore, we do not include the effect of emergency surgeries on the surgery schedule in this research.

Semi-urgent surgeries have to be performed within 24 hours after arrival. This type of surgery does not have precedence over elective surgeries. Semi-urgent surgeries are started when all resources needed for the surgery are available. If during regular opening hours of the OR department the resources needed for the semi-urgent surgery are unavailable, it is performed after opening hours by a team available during the night. A semi-urgent surgery therefore only influences the elective surgery schedule if an elective surgery later during the day needs a resource in use for the semi-urgent surgery.

2.2.5 ICT at the hospital

The surgery schedule is monitored by a planning system called MCC. This system graphically displays the surgery schedule in a Gantt-chart. The information needed to schedule the surgeries is gathered from various other departments. We describe the process of scheduling the surgeries in the Section 2.2.2. In this chapter we separately describe the ICT related parts of the process and possible difficulties occurring during this part of the process.

Information regarding the surgeries that are to be scheduled has to be available to schedule surgeries. This information includes the expected duration of the surgeries, name of the patient, name of the surgeon, and the type of surgery to be performed. The information is available from different information systems in use at Isala klinieken. We describe the 6 information systems used most frequently at the OR department in Table 1.

Table 1. ICT systems in use at Isala klinieken

Information system	Function	Developed by
MCC	Surgery planning and database system	Meierhofer (Germany)
EriDanos	Electronic Patient Record	Isala klinieken, in-house
IZIS	Waiting list data and patient demographic information	Isala klinieken, in-house
Mediscore	Scores the ICU patients health	Itémedical
Ultragenda	Agenda for specialists	Ultragenda
IVAS	Financial registration of Diagnostic-Related Group (DRG)	Isala klinieken, in-house

Each of these information systems contain and collect data regarding patients and surgical procedures. They are all suitable to perform tasks specific to the department using it. The OR department requires specific information regarding patients and the surgical procedures that have to be performed. The required information has to be gathered by the OR department from the other information systems in use. Some of the information systems are linked, so the information is transferred automatically from one information system to another, however, not all information systems are. The information from the information systems that are not linked has to be manually transferred to the OR department to create the surgery schedule. During the process of transferring data manually, errors can easily be made. Information can be inaccurately copied, or overlooked. This causes difficulties creating a surgery schedule. The surgical schedule is based on the data available to the planner, so any incomplete or incorrect data can lead to conflicts when the surgical schedule is executed.

Summary of ICT

The surgery schedule is based on information gathered from various ICT systems in use at the hospital. The information has to be transferred from the different information systems to the OR department. Inconsistencies may occur during this process, leading to a schedule based on incomplete, incorrect or inaccurate data. The resulting schedule can be optimal or near optimal but during execution of the schedule conflicts may arise because of differences between the schedule and reality.

3 Problem Description

In this section we describe how surgeries are loaded and scheduled in the current practice of location SZ of hospital Isala klinieken. This is done by creating surgical schedules per specialty based on the information locally available to the administration departments of the specialties, and then merging these local schedules into one central surgical schedule. In Section 3.1 we describe the process of scheduling the surgeries, taking into account that a part of these surgeries requires an X-ray machine. In Section 3.2 we give a formal description of this problem.

3.1 Creating the Surgery Schedule

Surgery schedules are created one week in advance. The administration departments of the surgical specialties first create a provisional surgery schedule. This provisional surgery schedule contains the surgeries that have to be performed during the next week by the specialty. The administration department only takes into account the information available at the administration department locally. The administration department schedules as many surgeries as possible, within the surgical time available to the specialty. As information about general OR department resources (e.g. X-ray machines, OR personnel) is unavailable to the administration departments, these provisional schedules can cause problems when the central surgery planner merges them into one surgery schedule. The central planner tries to create a schedule that contains all the surgeries in the provisional schedules. However, if for example availability of the X-ray machines prohibits this (e.g. because it leads to scheduling surgeries outside the surgical time available to the specialty performing the surgery) surgeries can be removed from the schedule. As the decision to remove a surgery from the schedule is taken by the planner in collaboration with medical personnel, we assume for our model that all surgeries in the provisional schedule have to be scheduled in the central surgery schedule. In Section 4 we propose algorithms that create a surgery schedule centrally to avoid problems with availability of the X-ray machine.

As the availability of the X-ray machine can also cause problems during the execution of the surgery schedule (e.g. the oil stain effect, explained in Section 2.2.4) we propose algorithms in Section 4 to create surgery schedules aimed at avoiding these problems.

3.2 Formal Problem Description

The problem consists of scheduling a given set of $K\left(k=1\ldots K\right)$ surgeries, in $J\left(j=1\ldots J\right)$ operating rooms, over a fixed time horizon, discretized into $W\left(w=1\ldots W\right)$ weeks. As each week poses an independent problem, we describe the problem for one week.

The set $K_w \subset K$ denotes the surgeries that have to be carried out in week w. Each week $w \in W$ consists of $D\left(d=1\ldots D\right)$ days. The set of ORs available on day d is de noted by J_d. We refer to a combination of a day d and an OR j as an OR day, i.e. $\{(j,d) \mid j \in J_d\}$. The set $S\left(s=1\ldots S\right)$ consists of the surgical specialties. For each surgery k it is given by which specialty $s_k \in \{1,\ldots,S\}$ this surgery has to be performed. For each OR day $\left(j,d\right)$ it is specified to which surgical specialty $s \in \{1,\ldots,S\}$ the OR j is entirely dedicated on day d of the week: $ORDay_s = \{(j,d) \mid OR\ j\ on\ day\ d\ is\ assigned\ \ to\ specialty\ \ s\}$. The set $ORDay_{s,d}$

denotes the ORs on day d available to specialty s (where $\sum_s |ORDay_{s,d}| = J_d, \forall d$). The OR days are assigned to the specialties according to a schedule: the Room Opening Plan (ROP).

For each surgery $k \in K$ the expected total surgery duration μ_k is given. Some surgeries require an additional resource R from the hospital (e.g. an X-ray machine during surgery). Therefore, let subset $K_{R,w} \subset K_w$ contain all surgeries that require resource R in week $w \in W$. Resource R has to be available from the start of the surgery until the end of the surgery. There are C_R units of resource R available.

Each regular OR day starts at B and ends at E. If surgeries are performed after the end time of OR j on day d, we refer to this time as overtime $O_{j,d}$. In practice, the OR planner of Isala klinieken in coordination with medical personnel can decide to cancel surgeries if overtime is expected to occur. In our research however, as cancelling a surgery is only done in collaboration with medical personnel, we assume each surgery $k \in K$ has to be performed.

The problem now is to decide for each surgery on which OR day and at what time it is to be performed in order to minimize the expected total overtime $\sum_{j,d} O_{j,d}$. Note that this encompasses both the surgery loading and scheduling problem.

A surgery schedule is feasible if the following constraints are satisfied:

- Surgeries can only be scheduled in an OR day dedicated to the specialty that performs those surgeries.
- Surgeries can only be scheduled to start in an OR day in the interval $[B, E]$, i.e. the surgeries have to start during regular opening hours of the OR department.
- For surgeries that require an X-ray machine it holds that: the surgery can only be scheduled if an X-ray machine is available for this surgery, i.e. the number of X-ray machines in use at the same time does not exceed the number of available X-ray machines.
- Each surgery $k \in K$ has to be in the surgery schedule.

Summarizing, for each week w, we create a surgery schedule for the surgeries in K_w. The surgery schedule for week w gives for each surgery $k \in K_w$ in which OR j and on which day d the surgery has to be performed, and at what time the surgery is scheduled to start. For each surgery in the schedule the resource requirement is given.

4 Solution Description

In this section we propose solution algorithms for the loading and scheduling of surgeries at the hospital operating room department. In Section 4.1 we describe the general ideas behind the solutions and why we split the solution in two phases. In Section 4.2 and 4.3 we subsequently describe the two phases of the solution approach.

4.1 General solution description

As the X-ray machines often cause capacity problems during the execution of the surgery schedule, we propose scheduling algorithms that take this resource into account while loading and scheduling the surgeries. The surgery schedule is created one week in advance. For each surgery, we have to determine on which day and in which OR it will be performed. Therefore, we divide the problem into two phases. In Phase 1, we divide surgeries $k \in K_w$ over the days in that week, keeping in mind the ROP, such that the load of the X-ray machines is leveled during the days of that week. The outcome of this phase is that for each surgery, the day of the week the surgery will be performed is determined, and that the load of the X-ray machines is leveled. In Phase 2, it remains to assign the surgeries to an OR on the day they are performed and to schedule the surgeries in the OR (i.e., determine a start time for the surgeries).

For both phases, we explore multiple solution approaches. For each approach, we propose algorithms and we compare the performance of these algorithms in Section 5. The resource we include in our research is the X-ray machine. However, the algorithms we propose are generic and can be applied to any resource that is use during the surgery. For Phase 1, we develop two algorithms to assign the surgeries to a day of the week. For Phase 2, we propose three algorithms. These algorithms aim to solve difficulties associated with the X-ray machines. In Section 4.2 we describe the two algorithms for Phase 1. In Section 4.3 we describe the three algorithms for Phase 2.

4.2 Phase 1: level the load of the resources over the days of a week

This section describes the first phase of the loading and scheduling problem. For every independent sub problem (i.e. every week) the surgeries that have to be performed are given. The characteristics of these surgeries include surgical specialty, expected duration and whether or not the surgery needs an X-ray machine during surgery. The goal of this phase is to assign a day to each surgery, in compliance with the ROP, such that the use of the X-ray machines during the week is leveled. To level the load of the X-ray machines during the week, we want to achieve a load per day that is close to the average load per day in the week. This average load per day in week w is given by:

$$averageload_{R,w} = \frac{\sum_{k} \mu_k}{D}, \; k \in K_{R,w} \tag{1}$$

We introduce binary decision variables $X_{k,d,j}$, to indicate whether or not surgery $k \in K_w$ is assigned to day $d \in D$ and OR $j \in J$. If all decisions have been fixed, a load of the X-ray on every day of the week is given. We define $load_{R,d}$ as the total amount of time that the X-ray machines are in use on day d. This is calculated by adding the total surgery durations of all surgeries k assigned to day d requiring an X-ray machine:

$$load_{R,d,w} = \sum_{k \in K_{R,w}} \mu_k \cdot \sum_{j} X_{k,d,j} \tag{2}$$

To achieve a leveled load per day, we first assign the surgeries that require X-ray to the OR days in the week, such that the difference between the average load during that week and the actual load that day is minimized. Hence, the goal function of the first phase is:

$$\min \sum_{d \in D} \left| load_{R,d,w} - AvgLoadPerDay_{R,w} \right| \tag{3}$$

To minimize the effect on (3) caused by surgeries with a long duration, we load the surgeries according to LPT (Longest Processing Time). When all surgeries that require the X-ray machine are loaded, the surgeries that do not require the X-ray machine are loaded to the OR days. We describe this algorithm in Section 4.2.1. However, if a specialty has only one OR day available for surgeries during a week, the surgeries of that specialty can only be loaded on that OR day. If the surgeries of this specialty are the last surgeries that are loaded, this can have a negative effect on the goal function (i.e. the surgeries have to be loaded on that day, no matter what this does to the goal function). Therefore, we propose a second algorithm for this phase. The second algorithm first schedules the surgeries of specialties that have only one OR day available per week. We describe this algorithm in Section 4.2.2.

4.2.1 Algorithm 1 (level the load)

To avoid peak resource loads on certain days of the week, while other days in that week have a much lower load, this algorithm loads surgeries in one week on the days in the week, minimizing the difference between the average load that week and the load per day.

The first algorithm for this phase can be summarized as follows:

Step 1.

> *Group the surgeries based on whether or not they need an X-ray machine: group 1 contains all surgeries that require an X-ray machine, group 2 contains all surgeries that do not require an X-ray machine.*

Step 2.

> *Sort the surgeries in each group based on non-increasing expected total surgery duration.*
>
> *k* := *the first surgery in group 1.*

Step 3.

> *Calculate (1).*

Step 4.

> *Load k on the day (in compliance with the ROP) which has the lowest resource load so far. Remove this surgery from group 1.*

Step 5.

> *If group 1 still contains surgeries:*
>
> *k* := *the first surgery in group 1, continue with step 4*
>
> *Otherwise: k* := *the first surgery in group 2, continue with step 6.*

Step 6.

> *Load k on an appropriate OR day according to "best fit" (i.e. load on the OR day with the smallest, large enough gap). Remove k from group 2.*

Step 7.

If group 2 still contains surgeries:

k := the first surgery in group 2, continue with step 6.

Otherwise: STOP.

As a result, for every week all surgeries are now allocated to a day and an OR. It remains to schedule the loaded surgeries in such a way that the capacity restrictions are satisfied. This is done in Phase 2.

4.2.2 Algorithm 2 (level the load, single OR days first)

This algorithm resembles Algorithm 1, with the addition that Algorithm 2 takes into account the possibility that specialties have only one OR day available during the week. The surgeries of a specialty with only one OR day available this week have to be loaded on that OR day. Loading the surgeries of this specialty later during the algorithm can have a large impact on the X-ray load on that day. If this occurs on a later stage of the algorithm, the possibilities to level the load over the remaining days are limited. To avoid this effect, Algorithm 2 first loads the surgeries of any specialty with only one OR day available. The remaining surgeries that require an X-ray machine are then loaded to level the load during the week. Algorithm 2 can be summarized as follows:

Step 1.

Group the surgeries, based on whether or not they need an X-ray machine: group 1 contains all surgeries that require an X-ray machine, group 2 contains all surgeries that do not require an X-ray machine.

Step 2.

Sort the surgeries in each group based on non-increasing expected total surgery duration.

Step 3.

If specialties with exactly one OR day exist: load the surgeries of these specialties on that OR day and remove them.

Step 4.

Calculate (1).

k := the first surgery in group 1.

Step 5.

Load k on the OR day (with OR days available to the specialty that performs k) which has the lowest resource load so far. Remove this surgery from group 1.

Step 6.

If group 1 still contains surgeries: k := the first surgery in group 1, continue with step 4. Otherwise: k := the first surgery in group 2, continue with step 7.

Step 7.

Load k on the day (with OR days available to the specialty that performs k), according to "best fit". Remove k from group 2.

Step 8.

If group 2 still contains surgeries: k := the first surgery in group 2, continue with step 7.

Otherwise: STOP.

4.3 Phase 2: schedule surgeries on a day

The result of Phase 1 is that each surgery is assigned to an OR day. In the second phase, we continue with this solution, but we release the OR assignment. The surgeries remain assigned to the day they were assigned to in Phase 1, and we reschedule the surgeries on each day to maximize utilization and to minimize overtime while complying with X-ray capacity constraints. We propose three scheduling algorithms for this phase. The first algorithm schedules the surgeries that require an X-ray machine as early on the day as possible, minimizing the risk of capacity problems with the X-ray machine at the end of the day. We describe this algorithm in Section 4.3.1. The second and third algorithm both aim at minimizing the oil stain effect (we described this effect in Section 2.2.4). The second algorithm schedules the surgeries of a specialty that require the X-ray machine front-to-back in one OR, forming a sort of "train" of surgeries that require the X-ray machine. We described this algorithm in Section 4.3.2. The third algorithm also aims to form "trains" of surgeries that require an X-ray machine. However, this algorithm does not allow scheduling surgeries in overtime. If a “train” of surgeries is too long to fit in one OR day, the surgeries that do not fit are scheduled in another OR day if another OR day is available. We describe this algorithm in Section 4.3.3.

4.3.1 Algorithm 3 (schedule X-ray surgeries as early as possible)

Overtime can occur when resource availability problems arise near the end of the day. Algorithm 3 aims to minimize this effect by scheduling the surgeries that require an X-ray machine as early on the day as possible. This way, when surgeries that require an X-ray machine run late, or semi-urgent surgeries that require an X-ray machine come in during the day, the effect should be minimal. The steps in the algorithm are as follows:

Step 1.

Group the surgeries loaded on this day, based on whether or not they need an X-ray machine: group 1 contains all surgeries that require an X-ray machine, group 2 contains all surgeries that do not require an X-ray machine.

Step 2.

Sort the surgeries in each group based on non-increasing expected total surgery duration.

Step 3.

Set Delta := *opening time of the OR department. k* := *the first surgery in group 1.*

Step 4.

Schedule k as early as possible, in a suitable OR. Remove k from group 1.

Step 5.

If surgery k uses the last X-ray machine available:

Delta := *the first time an X-ray machine becomes available. k* := *the first surgery in group 2. Continue with step 6.*

Otherwise: k := *the first surgery in group 1. Continue with step 4. (If no surgeries are in group 1: Delta* := *infinity, k* := *the first surgery in group 2, continue with step 7)*

Step 6.

If k can be scheduled such that the expected completion time of k is before Delta: schedule the surgery as early as possible, in a suitable OR. Remove k from group 2. k := the first surgery in group 2. Repeat step 6.

Otherwise, k := the first surgery in group 1. Continue with step 4.

Step 7.

If k can be scheduled such that the expected completion time of k is before Delta: schedule the surgery as early as possible, in a suitable OR. Remove k from group 2. k := the first surgery in group 2. Repeat step 7.

If no surgeries are in group 2: STOP.

To illustrate the effect of this algorithm, Figure 3 shows an example of a surgery schedule for one day, created according to Algorithm 3. Each column corresponds to an OR. The columns with green backgrounds are elective ORs, while the red background indicates an emergency OR. Columns with a grey background (for example in Figure 4) indicate ORs that are closed for the day. The bottom of the column corresponds to the opening time of the OR (i.e. 8:00), whereas the top of the column indicates the closing time of the OR (i.e. 17:00). Surgeries that end after the closing time are indicated by white bars along the side of the surgery. The coloring of the individual surgeries indicate whether or not that particular surgery requires an X-ray machine: red surgeries require an X-ray machine, yellow ones do not. The planning sequence of the X-ray surgeries is indicated by the arrows in the figure.

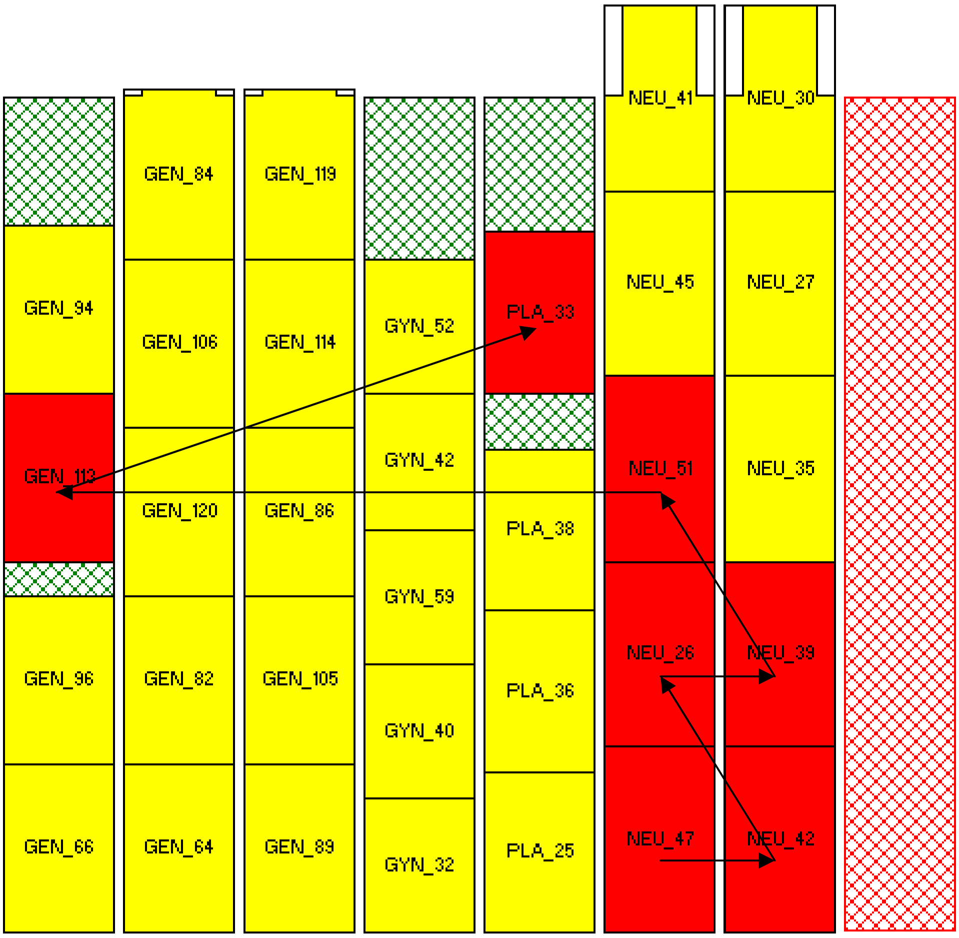

Figure 3: Example of a surgery schedule, created by applying Algorithm 3

4.3.2 Algorithm 4 (schedule "trains" of X-rays)

In Section 2.2.4 we described the "oil stain" effect: unexpected events in one OR can influence surgeries in other ORs. For example an X-ray machine is in use during a surgery in OR 1. If this surgery takes longer than expected, this can have to consequences. First, the surgery scheduled next in this OR has to wait. Second, the surgery that also requires the X-ray machine, scheduled in another OR, has to wait until the X-ray machine becomes available. Algorithm 4 aims to minimize this effect by forming a sort of "trains" of surgeries that require an X-ray machine. This way, when a surgery that requires X-ray takes longer than expected, only the surgery in the same OR is delayed. This algorithm can be summarized as follows:

Step 1.

> *Group the surgeries loaded on this day based on whether or not they need an X-ray machine: group one contains all surgeries that require an X-ray machine, group 2 contains all surgeries that do not require an X-ray machine.*

Step 2.

Sort the surgeries in each group based on non-increasing expected total surgery duration.

Step 3.

Set Delta := opening time of the OR department. k := the first surgery in group 1.

Step 4.

Schedule k as early as possible, after Delta, in a suitable OR. Remove k from group 1. Schedule the surgeries of the same specialty in group 1 in the same OR. Remove them from group 1.

Step 5.

Delta := the first time an X-ray machine becomes available. k := the first surgery in group 1. Continue with step 4.

If no surgeries are in group 1: k := the first surgery in group 2. Continue with step 6.

Step 6.

Schedule k as early as possible, in a suitable OR. Remove k from group 2. k := the first surgery in group 2. Repeat step 6.

If no surgeries are in group 2: STOP.

In Figure 4 we present an example of a surgery schedule created by applying Algorithm 4.

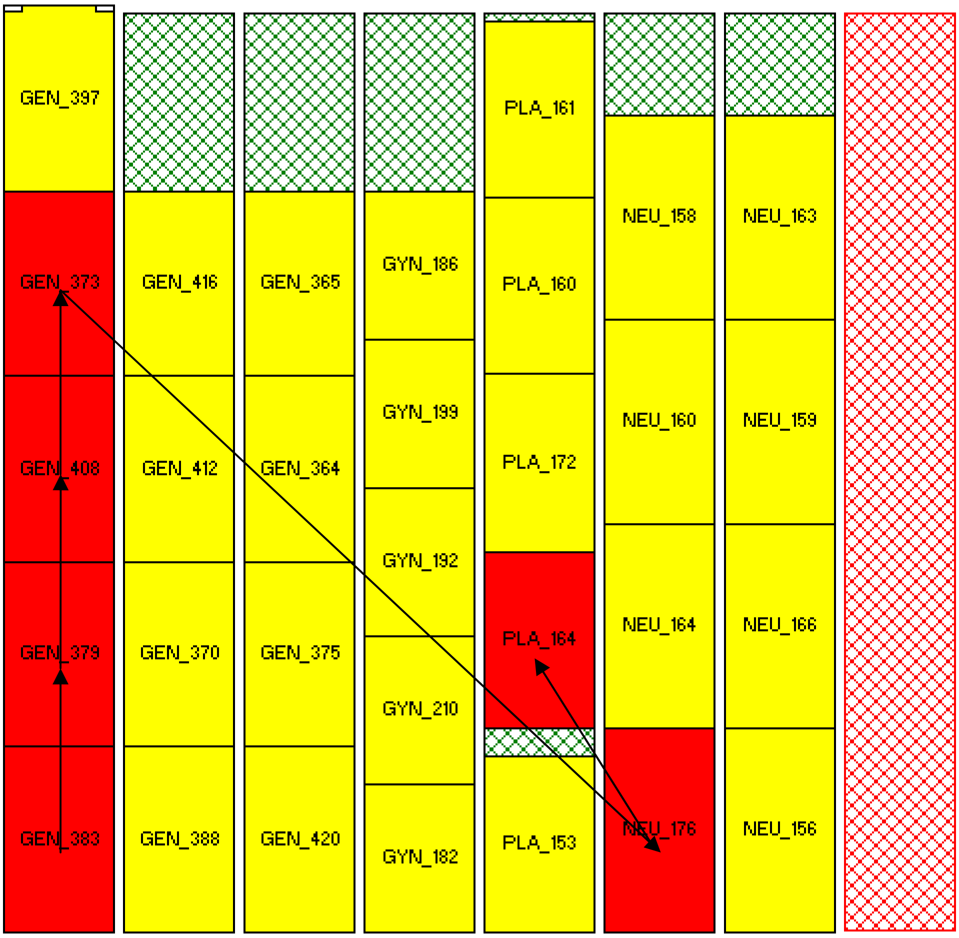

Figure 4: Example of a surgery schedule, created by applying Algorithm 4

4.3.3 Algorithm 5 (schedule "trains" of X-rays without scheduling in overtime)

The approach of Algorithm 5 is similar to that of Algorithm 4, with one addition. In Algorithm 4, it can occur that the surgeries in the "train" are scheduled in overtime, as the surgeries that require an X-ray machine are all scheduled back-to-front in one OR. To determine the effects of allowing the "trains" to be scheduled in overtime, this algorithm allows no scheduling in overtime. The steps in Algorithm 5 can be summarized as follows:

Step 1.

Group the surgeries loaded on this day based on whether or not they need an X-ray machine: group 1 contains all surgeries that require an X-ray machine, group 2 contains all surgeries that do not require an X-ray machine.

Step 2.

Sort the surgeries in each group based on non-increasing expected total surgery duration.

Step 3.

k := *the first surgery in group 1.*

Step 4.

Schedule k, as early as possible after Delta, in a suitable OR. Remove k from group 1.k:= the next surgery of the same specialty in group 1. If k fits in the same OR without creating overtime: schedule k in the same OR. Otherwise, schedule k in another suitable OR day, as early as possible. Remove k from group 1. Repeat step 4. If no surgeries are in group 1: continue with step 5.

Step 5.

k := *the first surgery in group 2.*

Step 6.

Schedule k as early as possible, in a suitable OR. Remove k from group 2. Continue with step 5.

If no surgeries are in group 2: STOP.

In Figure 5 we present a surgery schedule created by applying Algorithm 5.

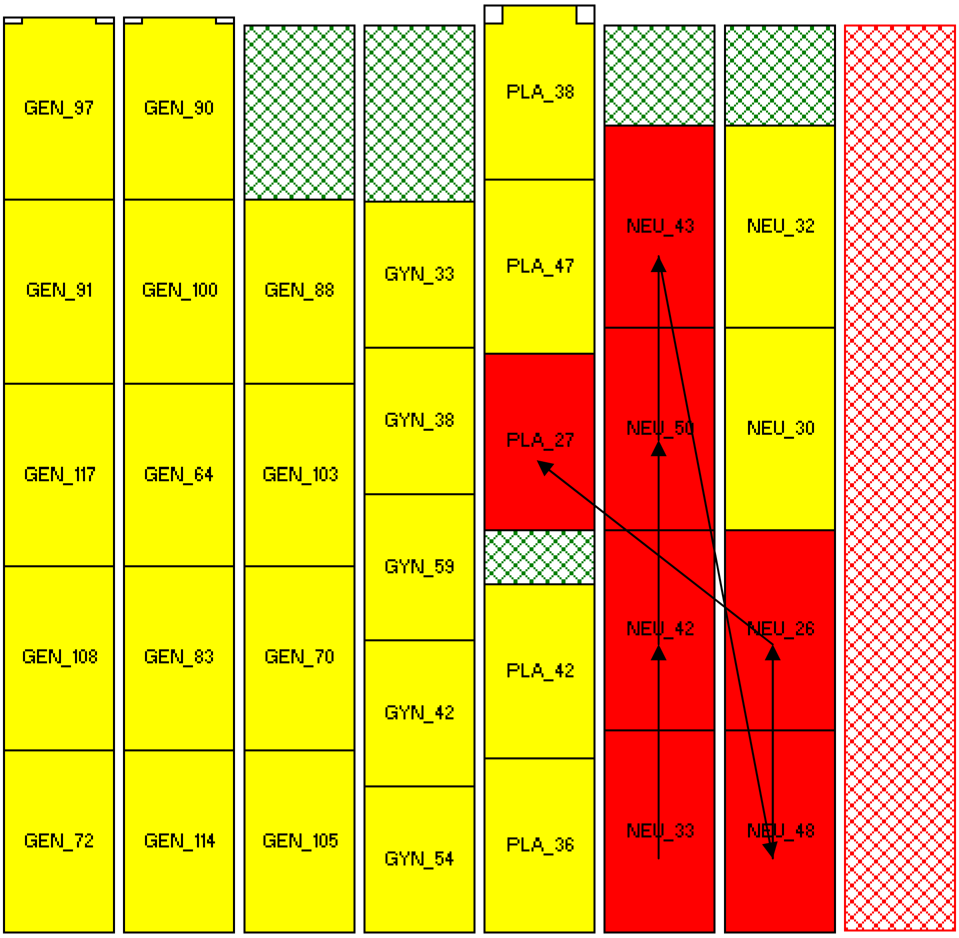

Figure 5: Example of a surgery schedule, created by applying Algorithm 5

Summary of the solution algorithms

Scheduling surgeries per week at location SZ of hospital Isala klinieken is decomposed into two phases. In Phase 1 we level the load of the X-ray over the days of the week. For this phase we developed two algorithms. Both Phase 1 algorithms aim to achieve a load per day as close as possible to the average load per day. In Phase 2 the surgeries are scheduled per day. For this phase we developed 3 algorithms, aimed at minimizing overtime and maximizing the utilization of the OR department. Table 2 summarizes the phases, corresponding algorithms and a short description of the algorithms.

Table 2. Overview of the phases and algorithms

Phase	Algorithm	Description
1	1	level the load
1	2	level the load, single OR days first
2	3	schedule X-ray surgeries as early as possible
2	4	schedule “trains” of X-rays
2	5	schedule “trains” of X-rays without scheduling in overtime

5 Numerical Experiments

This section describes the numerical experiments we perform to test the solutions we propose in Section 4. We describe how we gathered and analyzed the data from Isala klinieken in Section 5.1. We describe how we use these data to test the proposed solutions in Section 5.2. In Section 5.3 we give the results of the tests. To determine the behavior of the algorithms under varying circumstances (e.g. more semi-urgent surgeries arrive or the duration of the surgeries is determined per surgery type instead of per specialty) we perform simulations based on multiple fictional data instances in Section 5.4.

5.1 Numerical data

The surgeries in the surgery schedule are generated based on characteristics of actual surgeries performed at location SZ in the period 01-2006 until 07-2007. In this section, we determine the characteristics of the elective surgeries: mean μ, standard deviation σ, and the percentage of surgeries per specialty of the total number of surgeries. We present the results of the analysis in Table 3.

Table 3. Mean and Standard Deviation of the Total Surgery Duration per Specialty

Specialty	Number of procedures (%)	Mean μ (minutes)	Standard deviation σ (minutes)
General Surgery	42	99	60
Gynecology	21	77	42
Plastic Surgery	17	94	83
Neurosurgery	18	110	72
Orthopedic Surgery	1	114	70
Children’s Surgery	1	30	14

Appendix A gives the exact calculations and analyses that result in these numbers. As the mean of the total surgery duration is based on the actual surgery duration from start to end, it does not include changeover time. The hospital planning information system plans 10 minutes of changeover time after each surgery. For the simulations, we therefore add 10 minutes to the expected total surgery duration of each surgery. To compare the utilization calculated in the simulation with the utilization as it is used in the hospital, the changeover times of each surgery has to be subtracted from the total surgery time performed within regular opening hours of the OR department.

The number of specialties and the descriptives can be adjusted in the software. This way, for example the effect of changing surgery times and new specialties can be explored easily. Also, the total number of surgeries can be adjusted and the effects of an increasing patient volume can be investigated.

At location SZ, two identical parallel X-ray machines are available on each day. For each surgery, we determine whether this surgery requires an X-ray machine, based on the percentage of the specialty surgery volume that requires an X-ray machine. We determined this percentage per specialty in collaboration with the hospital's OR planner. Table 4 presents the percentage for all specialties $s \in S$ and the semi-urgent surgeries.

Table 4. X-ray probabilities per Specialty

	X-ray surgeries (%)
General Surgery	15
Gynecology	1
Plastic Surgery	11
Neurosurgery	50
Orthopedic Surgery	95
Children Surgery	1
Semi-urgent Surgery	40

In this research, we focus on one resource: X-ray machines. The solution algorithms and simulation however are set up in such a way that surgery schedules can be optimized based on other resources (e.g. surgery personnel and recovery beds) as well. The percentages can be changed as well, for example to explore the effects of changing surgery characteristics (e.g. medical specialists expect to perform more surgeries that require an X-ray machine).

Surgeries can only be performed in an OR assigned to the specialty that performs the surgery. ORs are assigned to specialties per day. The division of ORs per specialty $s \in S$ on each day $D\,(d = 1 \ldots D)$ is given by Table 5.

Table 5. Room Opening Plan at location SZ of Isala klinieken

	Monday	Tuesday	Wednesday	Thursday	Friday	Total
General Surgery	3	3	2	3	2	13
Gynecology	1	2	1	1	1	6
Plastic Surgery	1	1	1	1	1	5
Neurosurgery	2	0	1	2	1	6
Orthopedic Surgery	0	1	0	0	0	1
Children Surgery	0	0	0	0	1	1
Total	7	7	5	7	6	32
Emergency	1	1	1	1	1	5

As the number of ORs, opening and closing time of the OR department, and the specialties the ORs are assigned to can be adjusted in the software, for example the effects of opening or closing an extra OR and changing the allocation of ORs to specialties can be easily explored.

To simulate the arrival of semi-urgent surgeries, we need to know the expected number of surgeries arriving during the day, and the distribution function of the surgery duration of the semi-urgent surgeries. We give the complete analysis of semi-urgent surgeries performed at location SZ of Isala klinieken in Appendix F. Table 6 gives the results of these analyses.

Table 6. Descriptives of the semi-urgent surgeries

	Surgeries in regular hours	Mean (minutes)	Standard deviation (minutes)
Semi-urgent surgeries	4	74.09	48.30

Table 7 summarizes the characteristics of each simulation instance.

Table 7. Summary of the characteristics of one instance

Number of elective surgeries	7,500
Specialties	6
Expected elective surgery time (hours)	13,121
Elective OR capacity (hours)	14,976
Expected number of semi-urgent surgeries	1,040
Expected semi-urgent surgery time (hours)	1,284
Emergency OR capacity (hours)	2,340
Weeks per year	52

5.2 Experiments

To determine the performance of the scheduling algorithms we propose in Section 4 we simulate the execution of the surgery schedules and we compare the results with the current practice of surgery scheduling at the hospital. The surgery schedules are based on the expected surgery duration. Although this expected surgery duration is accurately estimated, based on historical data, in reality the actual surgery duration differs from the expected surgery duration. Therefore, to perform simulations, we also need the standard deviation in the surgery duration. The simulation consists of executing the surgery schedules with the arrival of semi-urgent surgeries and deviations from expected surgery duration. All algorithms and simulations have been implemented in the Borland Delphi programming language and run on a laptop pc. For each day, the recipe of the simulation is as follows:

At 8:00, the elective surgeries scheduled to be performed first in each OR are given their actual surgery duration by drawing a random value from the distribution function of that surgery. Also, the semi-urgent surgeries for that day are generated by drawing arrival times from the distribution function of the number of semi-urgent surgeries. New semi-urgent surgeries are generated until the arrival time of the next surgery is later than the closing time of the OR department. Along with the arrival time of the semi-urgent surgery, we also determine the duration of this surgery and whether or not it requires an X-ray machine. With these surgeries (i.e. the first elective and all semi-urgent surgeries for this day), the day is started. Each time an elective surgery is finished, the next surgery scheduled in that OR is given its actual surgery duration. If this surgery needs an X-ray machine, the availability of the X-ray machines is checked. If the X-ray machine is available, the surgery is started. If it is not available, then the surgery has to wait until an X-ray machine becomes available. The same goes for the semi-urgent surgeries: if a semi-urgent surgery requires an X-ray machine, the surgery is started, in the OR it is scheduled in, depending the availability of an X-ray machine. Additionally, a semi-urgent surgery can only be started after the arrival time determined for it.

As the decision about cancelling a surgery is left to the planner and medical personnel, we assume that all surgeries that are in the schedule have to be performed.

As we have developed two loading and three scheduling algorithms, we perform 2*3=6 simulations to compare the performance of these algorithms. We present the results per method. The first "base" method represents the current way of scheduling surgeries at location SZ. Each method consists of 2 algorithms, consistent with the algorithms we described in Section 4. In Table 8 we present the algorithms used per method.

Table 8. Algorithms used to load and schedule surgeries for the simulations

Method	Phase 1	Phase 2
0	None	None
1	Algorithm 1	Algorithm 3
2	Algorithm 1	Algorithm 4
3	Algorithm 1	Algorithm 5
4	Algorithm 2	Algorithm 3
5	Algorithm 2	Algorithm 4
6	Algorithm 2	Algorithm 5

Each simulation run represents one year, consisting of 52 weeks with five regular working days per week. For each run, the daily surgery schedules are identical. Due to the random drawing of surgery durations and semi-urgent surgery arrivals, each run has a different result. To determine the number of runs necessary to draw reliable conclusions, we apply [Law & Kelton, 2000] to the total duration of semi-urgent surgeries in one run. At a 90% confidence level with relative error $\gamma = 0.05$, we find that the required number of runs to draw statistically significant conclusions is 1,394.

5.3 Results

The goal of the research is to optimize the efficiency of the OR department. Key performance indicators are the amount of overtime and the utilization of the ORs. This section presents the results of the simulations described in Section 5.1 and 5.2. We present the results of the key performance indicators overtime and utilization and on additional performance indicators total waiting times for surgeries and waiting times for surgeries, solely caused by X-ray restrictions. Table 9 presents the performance of the methods based on overtime and utilization.

Table 9. Key performance indicator results of the simulations

Method	Avg. overtime elective surgeries in min/day (sd)	Utilization elective surgeries in %	Avg. overtime semi-urgent surgeries in min/day (sd)	Utilization semi-urgent (%)
0	276 (13)	79.6	62 (5)	45.4
1	250 (12)	80.4	61 (5)	45.6
2	246 (12)	80.5	59 (5)	45.9
3	239 (11)	80.7	60 (5)	45.7
4	250 (12)	80.4	61 (5)	45.6
5	246 (12)	80.5	59 (5)	45.9
6	239 (11)	80.7	60 (5)	45.7

The first striking result is that algorithms 1 and 2 (i.e. both Phase 1 algorithms) give the same results. The difference is made by the Phase 2 algorithms. In Section 5.4 we investigate this effect. Furthermore, methods 2, 3, 5 and 6 decrease the waiting time and increase the utilization further than methods 1 and 4. As we already concluded the difference is made in Phase 2, this leads to the conclusion that algorithms 4 and 5 perform better than algorithm 3.

We also compare the performance of the methods on total waiting time and waiting time induced by resource (non-)availability. Table 10 presents the results for these performance indicators.

Table 10. Results in terms of waiting time

Method	Avg. waiting time elective surgeries in min/surgery (sd)	Avg. resource-induced waiting time elective surgeries in min/surgery (sd)	Decrease resource induced waiting time (%)	Avg. waiting time semi-urgent in min/surgery (sd)	Avg. resource-induced waiting time semi-urgent in min/surgery (sd)
0	31 (1.2)	4.0 (0.42)	-	56 (4.5)	17 (2.1)
1	29 (1.2)	2.2 (0.20)	44	55 (4.6)	17 (2.1)
2	27 (1.1)	0.8 (0.11)	80	50 (4.4)	12 (1.8)
3	28 (1.1)	1.2 (0.14)	71	52 (4.3)	14 (1.9)
4	29 (1.2)	2.2 (0.20)	44	55 (4.4)	17 (2.0)
5	27 (1.1)	0.8 (0.11)	80	50 (4.4)	12 (1.8)
6	28 (1.1)	1.2 (0.14)	71	52 (4.3)	14 (1.9)

In Table 10, again no large differences between algorithm 1 and 2 occur. The largest waiting time reduction is achieved when Method 2 and Method 5 are applied. Since both Method 2 and Method 5 use Algorithm 4, we conclude the best Phase 2 algorithm is Algorithm 4. This algorithm reduces the average time a surgery is waiting for a resource from 4.0 minutes to 0.8 minutes (i.e. 80% reduction in time the surgery has to wait to start as the X-ray machine is unavailable).

5.4 Sensitivity analysis

To test the performance of the algorithms under various circumstances, we perform multiple simulations based on fictional data instances. In the previous section we determined that the best performance is achieved by applying methods 2, 3, 5, and 6. This section compares the performance of these methods applied to various circumstances.

Influence of defining multiple surgical groups for the specialty that uses X-ray most

To investigate the influence of the X-ray load on the algorithms, we perform simulations with multiple surgical groups for the specialty with the largest X-ray load. Table 11 presents the use of the X-ray machine per specialty.

Table 11. X-ray usage per specialty

	Surgery volume (%)	# surgeries per year	Average surgery duration (min)	Surgeries that require X-ray (%)	X-ray usage per year (min)
General Surg.	42	3,150	109	15	5,1502.50
Gynecology	21	1,575	87	1	1,370.25
Neurosurg.	1	1,350	120	50	81,000.00
Plastic Surg.	18	1,275	104	11	14,586.00
Children’s Surg.	1	75	40	1	30.00
Orthopedic Surg.	17	75	124	95	8,835.00
Total	100	7,500			

From Table 11 we conclude Neurosurgery uses most X-ray minutes per year. To investigate the effect of defining more surgery groups (i.e. more types of surgeries with different average surgery duration) we split Neurosurgery into 3 groups. The three groups all have different expected surgery durations, but they all have the same standard deviation. By defining the three averages symmetrically around the actual surgery duration of specialty Neurosurgery, the total expected time Neurosurgery performs surgery does not change. As the three groups indicate three different types of surgery with better defined surgery duration, we divide the standard deviation by two. Table 12 gives the instance data for Neurosurgery.

Table 12. Surgery duration and standard deviation for Neurosurgery split into three groups

	Total surgery duration	Standard deviation
Neurosurgery	60	36
	120	36
	180	36

Table 13 presents the results of simulating the execution of the schedules based on these instance.

Table 13. Performance of the algorithms with Neurosurgery split into three groups

Method	Avg. waiting time elective in min/surgery (sd)	Avg. resource-induced waiting time elective in min/surgery (sd)	Decrease resource induced waiting time (%)	Avg. waiting time semi-urgent in min/surgery (sd)	Avg. resource-induced waiting time semi-urgent (min/surgery)
0	29 (1.2)	5.3 (0.44)	-	57 (4.5)	18 (2.2)
2	25 (1.1)	0.9 (0.12)	84	50 (4.3)	12 (1.8)
3	26 (1.1)	1.2 (0.13)	78	53 (4.5)	15 (1.9)
5	25 (1.1)	0.9 (0.12)	84	50 (4.3)	12 (1.8)
6	26 (1.1)	1.2 (0.13)	78	53 (4.5)	15 (1.9)

The results in Table 13 indicate there are no differences between the Phase 1 algorithms. The largest decrease in resource induced waiting time is achieved by applying Method 2 and Method 5. Therefore, we conclude Algorithm 4 has the best performance, and the performance of the algorithm increases if the surgery duration is estimated to more detail.

Influence of using better estimates of the surgery duration

In the original instance we describe in Section 5.1, every surgical specialty performs one type of surgery. These surgeries are described by the mean surgery duration and the standard deviation of the specialty that performs the surgery. To investigate the effect of having multiple surgical groups per specialty on the performance of the algorithms, we split each surgical specialty in two surgical groups. Each first surgical group of a specialty has a reduced mean surgery duration, while each second group has an increased mean surgery duration. As we want to investigate the effect of the groups without altering the total amount of surgery time, the decrease in the mean surgery duration of the first groups is equal to the increase in the mean surgery duration of the second group. The standard deviation of each surgical group is set to half the standard deviation of the surgical specialty and, thus, the groups represent smaller groups of surgeries with better defined surgery durations. Table 14 gives the descriptives of the surgical groups.

Table 14. Surgery duration and standard deviation split per specialty

	Group	Mean surgery duration	Standard deviation
General Surgery	1	79	30
	2	139	30
Gynecology	1	57	21
	2	117	21
Neurosurgery	1	90	36
	2	150	36
Plastic Surgery	1	74	41
	2	134	41
Children's Surgery	1	20	7
	2	60	7
Orthopedic Surgery	1	94	35
	2	154	35

The results for this instance are presented in Table 15.

Table 15. Results for the simulation with specialties split into two groups

Method	Avg. waiting time elective surgeries in min/surgery (sd)	Avg. resource-induced waiting time elective surgeries in min/surgery (sd)	Decrease resource induced waiting time (%)	Avg. waiting time semi-urgent surgeries in min/surgery (sd)	Avg. resource-induced waiting time semi-urgent in min/surgery (sd)
0	19 (0.8)	4,9 (0.43)	-	57 (4.5)	18 (2.1)
2	16 (0.6)	0,7 (0.08)	86	50 (4.4)	12 (1.7)
3	16 (0.6)	0,8 (0.09)	83	52 (4.5)	13 (1.8)
5	16 (0.6)	0,7 (0.08)	86	50 (4.3)	12 (1.6)
6	16 (0.7)	0,8 (0.09)	83	52 (4.4)	13 (1.8)

Again, the differences between Algorithm 1 and Algorithm 2 (both Phase 1 algorithms) are relatively small. The difference is made by the Phase 2 algorithms. The largest improvement is made by Algorithm 4: a reduction in resource induced waiting time from 4.4 to 0.6 minutes per elective surgery. Also, the reduction in resource induced waiting time is larger than in the instance we calculated from the actual data of the hospital. This indicates the performance of the algorithms increases as the surgery durations are estimated to more detail.

Influence of the number of semi-urgent surgeries that come in during the day?

An average of 10 semi-urgent surgeries arrives during 24 hours. We are interested in the performance of the algorithms if these semi urgent surgeries arrive somewhat concentrated during regular hours. We test the performance of the algorithms in this situation by simulating 5 semi-urgent surgery arrivals during regular opening hours of the OR department, instead of 4. Table 16 presents the results of simulating this instance.

Table 16. Performance of the algorithms with 5 semi-urgent arrivals per day

Method	Avg. waiting time elective surgeries in min/surgery (sd)	Avg. resource-induced waiting time elective in min/surgery (sd)	Decrease resource-induced waiting time (%)	Avg. waiting time semi-urgent surgeries in min/surgery (sd)	Avg. resource-induced waiting time semi-urgent surgeries in min/surgery (sd)
0	31 (1.3)	4,6 (0.50)	0	75 (5.4)	21 (2.4)
2	28 (1.1)	0,9 (0.12)	80	69 (5.1)	16 (2.0)
3	28 (1.2)	1,4 (0.15)	70	71 (5.2)	18 (2.2)
5	28 (1.1)	0,9 (0.12)	80	69 (5.1)	16 (2.0)
6	28 (1.2)	1,4 (0.15)	70	72 (5.2)	18 (2.1)

The results in Table 16 show a higher average waiting time for both elective and semi-urgent surgeries compared with the results in Section 5.3. This is due to the higher number of semi-urgent surgeries. However, the relative improvement in resource-waiting time achieved by applying the optimization methods is even higher: 70% improvement for both methods 3 and 6 and 80% improvement by applying both methods 2 and 5. Therefore, we conclude the algorithms can cope with higher number of semi-urgent surgeries.

6 Conclusions and reflections

We have proposed two-phase solution methods for loading and scheduling surgeries with physical resource constraints. The goal of the research was to increase the efficiency of the OR department in terms of utilization and overtime. We have shown that these methods can significantly increase the utilization and decrease the amount of overtime of the OR department. Furthermore, these methods decrease the time patients and personnel have to wait between surgeries. The best performing combination of algorithms increases utilization of the seven elective ORs from 79.6% to 80.5%. Overtime for the elective ORs is decreased from 276 to 246 minutes per day.

The best algorithm to level the load of the surgeries during the week is Algorithm 2. This algorithm levels the load of the resource over the days of the week. The best overall results are obtained when this loading algorithm is combined with Algorithm 4. This algorithm schedules the surgeries as clustered as possible. The combination of these algorithms positively affects patients and OR personnel: waiting times for elective surgeries decrease from 31 to 27 minutes per surgery and the resource induced waiting time for elective surgeries decreases from 4.0 to 0.8 minutes per surgery.

The surgery schedule resulting from Algorithm 4 shows “trains” of surgeries that require a physical resource. In this research we applied the algorithms to schedule surgeries that require an X-ray machine. As the loading and scheduling of surgeries is done centrally, this way of scheduling a resource can also be applied to other resources (e.g. surgery personnel). Adjusting the scheduling algorithms to include multiple resources is subject of further research.

We developed scheduling algorithms that increase the OR departments efficiency by reducing waiting times between surgeries. There are many practical constraints influencing the possibilities to adjust the surgery schedule. Therefore, further research should also focus on implementing constraints such as surgeon availability and IC bed capacity.

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List of terms

CSD
Central Sterilization Department (Dutch: Centrale Sterilisatie Afdeling)

DRG
Diagnostic-Related Group (Dutch: Diagnose-Behandel Combinatie)

Elective Surgery
Scheduled surgery [Coëlho, 2000]

Gastroenterology
The branch of medicine concerned with the study of disorders affecting the stomach, intestines, and associated organs [Coëlho, 2000]

LPT
Longest Processing Time scheduling rule

MCC
Surgery planning system used at Isala klinieken.

Neurosurgery
The surgical discipline focused on surgery on the central and peripheral nervous system [Coëlho, 2000].

Oncology
The branch of medicine concerned with tumors [Coëlho, 2000].

Orthopedic surgery
The branch of surgery concerned with the musculoskeletal system [Coëlho, 2000].

Pathologist-anatomist
Researcher concerned with changes in patient tissue and organs [Coëlho, 2000] (Dutch: patholoog-anatoom).

Plastic surgery
Specialty concerned with surgical techniques to change, enhance or reinforce parts of the patient’s body [Coëlho, 2000].

ROP
Room Opening Plan (Dutch: Kamer Openstellings Plan)

SZ
Location Sophia of the Isala Klinieken (Dutch: Sophia Ziekenhuis).

Urology
The field of medicine focused on the urinary tracts of males and females, and on the reproductive system of males [Coëlho, 2000].

WL
Location Weezenlanden of Isala Klinieken (Dutch: Weezenlanden).

Appendix A: Data analysis

To test the solution algorithms we propose in Section 4, we use the algorithms to create fictional surgery schedules. To fill the fictional surgery schedules with surgeries, we create surgeries per specialty according to the number of surgeries this specialty actually performs at the hospital. To schedule the surgeries, we also need the expected total surgery duration. To test the fictional surgery schedules, we perform discrete event simulations in Section 5. For these simulations, we need the type of distribution of the total surgery duration, and in addition to the expected surgery duration, we need the standard deviation of the total surgery duration. We derive these data from actual surgery data stored in the hospital's data repository. From this data repository, we retrieve data regarding surgeries performed in the period 01-2006 until 07-2007. The analysis consists of three parts. In Appendix A1 we begin by selecting from the database the surgeries of interest to us (excluding for example surgeries performed at the day treatment center). As we want to determine the distribution type and the descriptives of the data, we now need to check whether the data is suitable to perform the tests we need to determine the distribution and descriptives. We do this by performing an outlier analysis in Appendix A2. In the third part of the analysis we determine the distribution types and descriptives of the data. We describe this in Appendix A3.

A1 Pre selection

The analysis is based on surgery data from January 2006 until July 22nd, 2007. During this period, 46,173 surgical procedures were performed at both locations of Isala klinieken. Surgery information from the surgery planning system, MCC, is stored in a central database. Since we are only concerned with clinical procedures performed at location SZ during regular working hours, we exclude all procedures performed at location WL, semi-urgent surgeries, procedures performed during the weekend, and all non-clinical procedures (e.g. procedures performed at the day treatment center). After removing these surgeries, 11,591 surgical procedures remain in the dataset. This dataset now contains surgeries performed by 17 surgical specialties. Some specialties that perform surgeries at SZ only perform a very small percentage of all surgeries. These specialties have no OR days in the regular ROP: they occasionally get assigned one or even one half OR day. As we only consider specialties that have OR days in the regular ROP, we need to exclude surgeries performed by other specialties. Table 17 gives the percentage of the total amount of surgeries the specialties account for.

Table 17. Percentage of all surgeries per specialty

	Frequency	Percent	Cumulative percent
General Surgery	4,739	40.9	40.9
Gynecology	2,368	20.4	61.3
Neurosurgery	1,995	17.2	78.5
Plastic Surgery	1,952	16.8	95.4
Ear, Nose, Throat	181	1.6	96.9
Children’s Surgery	150	1.3	98.2
Orthopedic Surgery	86	0.7	99.0
Urology	79	0.7	99.6
Radio Therapy	20	0.2	99.8
Gastroenterology	6	0.1	99.9
Jaw Surgery	4	0.0	99.9
Anesthesia	3	0.0	99.9
Internal Medicine	3	0.0	100.0
Psychiatry	2	0.0	100.0
Dermatology	1	0.0	100.0
Radiology	1	0.0	100.0
Eye Surgery	1	0.0	100.0
Total	11,591	100.0	

We select the six largest specialties: General Surgery, Gynecology, Neurosurgery, Plastic Surgery, Children’s Surgery and Orthopedic Surgery. Although specialty Ear, Nose, Throat is larger than Children’s Surgery and Orthopedic Surgery, it is excluded from the selection as in 2007 this specialty no longer performs elective procedures at location SZ (i.e. this specialty has no regular OR days in the ROP). The six specialties we consider account for 98 % of the total number of surgeries. Table 18 gives the percentages of surgeries per specialty with respect to the total number of surgeries in the dataset of the six largest specialties.

Table 18. Percentage of surgeries per specialty (of the six largest specialties)

	Frequency	Percent	Cumulative Percent
General Surgery	4,739	42	42
Gynecology	2,368	21	63
Neurosurgery	1,995	18	81
Plastic Surgery	1,952	17	98
Children’s Surgery	150	1	99
Orthopedic Surgery	86	1	100
Total	11,290	100	

Summary of the pre-selection

In this research we consider surgeries performed in clinical ORs at location SZ. We analyze the data in the hospitals data repository to obtain information (e.g. average surgery duration, standard deviation of the surgery duration) regarding these elective, clinical surgeries at SZ. As the hospital data repository contains data regarding other surgeries (e.g. semi-urgent surgeries and surgeries performed at other locations), we first remove these other surgeries from the database. Furthermore, as we limit our research to surgeries performed by specialties that have regular OR days in the ROP, we remove the surgeries in the data repository performed by specialties without regular OR days in the ROP.

A2 Outlier analysis

In Appendix A1 we prepared the dataset for statistical analysis. To determine the parameters we need to create fictional surgery schedules and perform discrete event simulations, we need to analyze the data statistically. In this appendix we continue the analysis of the dataset of Appendix A1. After a pre selection of the surgeries, this dataset now contains 11,290 surgeries performed in the clinical ORs at location SZ. To determine the surgery parameters in Appendix A3, we first perform an outlier analysis on the surgeries in the dataset in this appendix. As we consider elective surgeries, we perform an outlier analysis on surgery start time, surgery end time and surgery duration. Surgeries with extreme surgery start or end times indicate these surgeries are not part of the regular, elective surgery schedule. Surgeries with extreme duration are checked for reliability, as the extreme duration can be a mistake made during data entry in the data repository.

A2.1 Start time analysis

11,290 Surgeries are in the database. A small fraction (less than 1 percent) of these surgeries is performed outside of regular working hours during week days: they are performed during the night. As no elective patients are scheduled for surgery during the night, we assume these surgeries are emergency patients. As we base our analysis on elective surgeries, these emergency surgeries must be excluded from further analysis.

Elective surgeries can end after regular opening hours of the OR department. For example: a surgery starts at 16:00 and ends at 18:00, so it starts during regular working hours, but ends outside of regular working hours. Although the end time of the surgery suggests it is an emergency surgery (performed outside of regular hours), it actually is an elective surgery. Therefore, we have to determine the time window in which the elective surgeries are performed. To determine the time window, the 11,290 surgeries in the dataset are sorted on non-decreasing start time, from early to late. Figure 6 shows the starting times of the anesthesia (i.e. the starting time of the surgery) of all 11,290 surgeries in the sorted dataset. The surgery number on the x-axis indicates the position of the surgery in the sorted dataset.

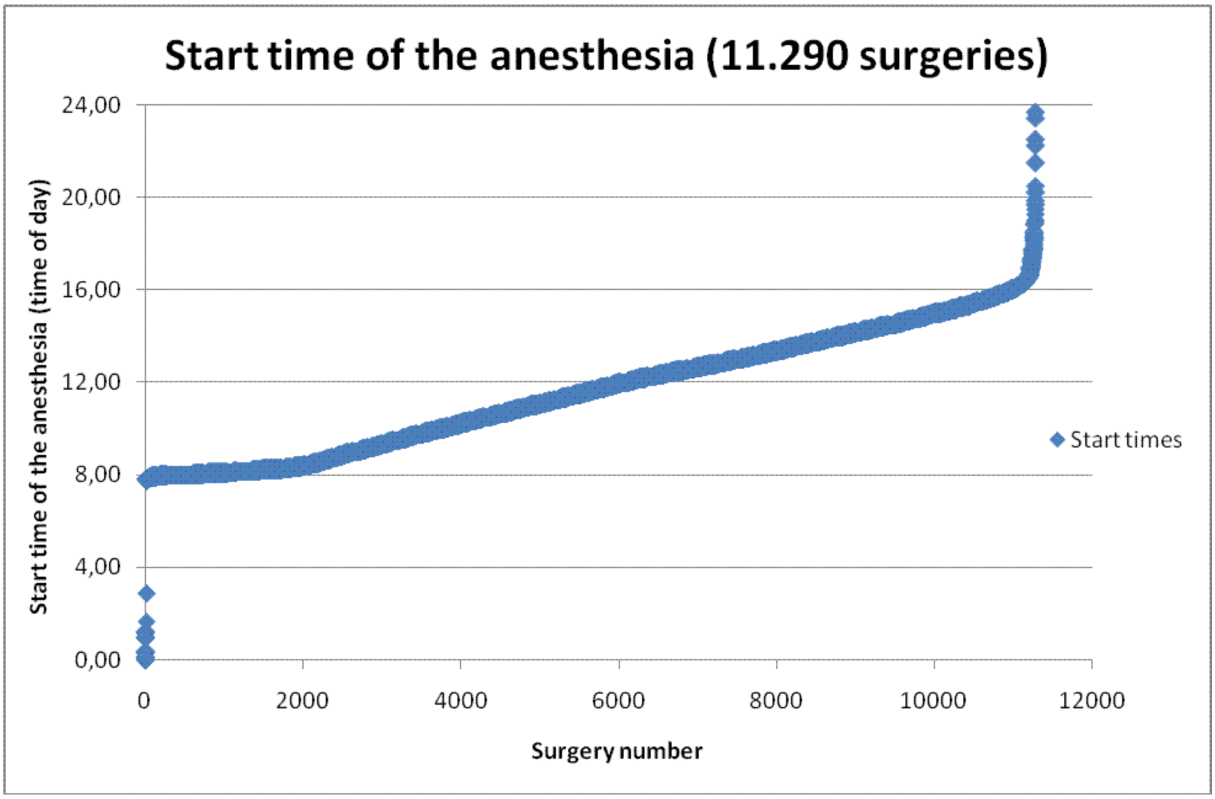

Figure 6: Start time of anesthesia for 11,290 surgeries performed at location SZ

Between 7:45 and 20:30 the starting times are very close together, with a maximum of 22 minutes apart. However, before 7:45 and after 20:30, the intervals between starting times are larger, some more than an hour apart. We assume these larger intervals indicate these surgeries are not part of the elective surgery schedule. As we want to analyze the elective surgeries, we exclude the 21 emergency surgeries that start before 7:45 or after 20:30. The dataset now contains 11,269 surgeries.

A2.2 End time analysis

To determine whether surgeries in the dataset end outside the regular opening hours of the OR department, we now sort the 11,269 surgeries in the dataset on non-decreasing end time of surgery. Figure 7 shows the plot of the end times of the 11.269 surgeries in the dataset. The surgery number on the x-axis again gives the number of the surgery in the sorted dataset.

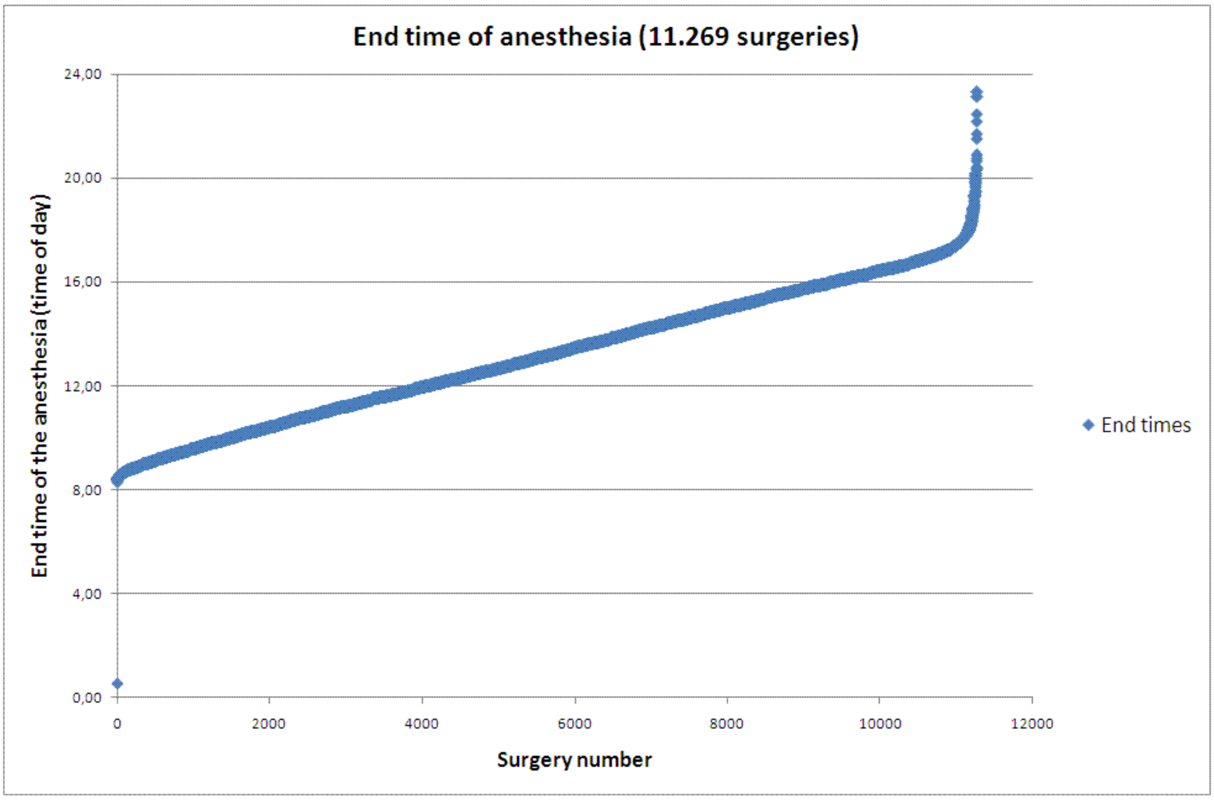

Figure 7: End time of anesthesia for 11,269 surgeries performed at location SZ

The end times of the surgeries are close together from 8:18 until 20:53, with a maximum of 15 minutes apart. Before 8:18 and after 20:53 the surgery end times are further apart, some more than an hour. We assume the surgeries with end times between 20:53 and 8:18 (i.e. during the night) are not elective surgeries. As we want to analyze elective surgeries, we exclude the 7 emergency surgeries that end between 20:52 and 8:18. The dataset now contains 11,262 surgeries.

A2.3 Surgery duration analysis

We analyze the surgery durations as we want to create fictional surgery schedules using based on actual surgery durations. Therefore, we want to analyze the data for any anomalies in surgery duration. For example an extremely long surgery duration (e.g. 16 hours) can indicate that it is incorrectly entered into the database, and therefore not reliable. To analyze the surgery duration, we first sort the 11,262 surgeries in the dataset on non-decreasing total surgery duration. Figure 8 shows the total surgery duration of the 11,262 surgeries in the dataset. The surgery number on the x-axis indicates the position of the surgery in the sorted dataset.

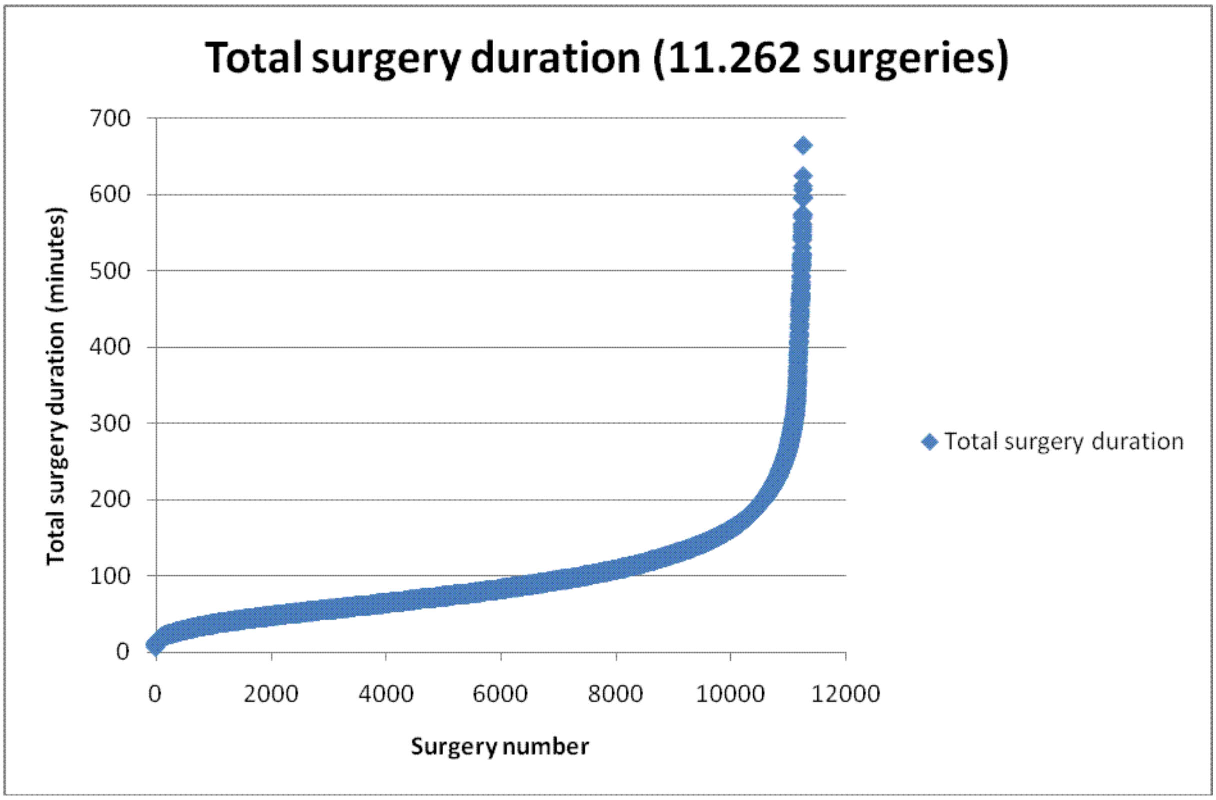

Figure 8: Total surgery duration of 11,262 surgeries performed at location SZ

A few of the surgeries with the longest duration stand out as the total surgery duration of those surgeries is much larger than the other durations. On closer, individual inspection however, these surgeries are complicated surgeries that actually took very long. As we want to base our fictional surgery schedule on actual data, we include the surgeries in the statistical analysis.

The dataset now contains 11,262 elective surgeries performed during regular hours in clinical ORs at location SZ. We want to base our fictional surgery schedules on these surgeries. To determine the amount of surgeries performed by each specialty in the dataset, we calculate the percentage of the total amount of surgeries per specialties. We present these percentages in Table 19.

Table 19. Six largest specialties, after removing surgeries performed during the evening and night

	Frequency	Percent	Cumulative Percent
General Surgery	4,730	42	42
Gynecology	2,363	20	62
Neurosurgery	1,990	18	80
Plastic Surgery	1,948	17	97
Children's Surgery	150	2	99
Orthopedic Surgery	81	1	100
Total	11,262	100	

Summary of the statistical selection

Based on extreme values of the surgery start time, surgery end time and total surgery duration we removed 28 surgeries from the dataset. The dataset now contains 11,262 elective surgeries, performed during regular working hours in the clinical ORs at location SZ. From the surgeries in the dataset, we can now determine the parameters we need to create fictional surgery schedules (e.g. average surgery duration) and to perform discrete event simulations (e.g. surgery duration standard deviations).

A3 Determine distribution type and descriptives

To create fictional surgery schedules, we need to know the average total surgery duration per specialty. To test the performance of the fictional surgery schedules, we perform discrete event simulations. Therefore, we also need the distribution type and the standard deviation of the surgery duration, so we can randomly draw values from the standard deviation. As the total surgery duration differs per surgical specialty, we determine the average, the standard deviation and the distribution type per surgical specialty. In Appendix A3.1 we determine the type of distribution of the total surgery duration. In Appendix A3.2 we determine the descriptives for this type of distribution.

A3.1 Determining distribution type

We determine the distribution type of the total duration of the surgeries per specialty. Other research suggests a normal or lognormal distribution [(Strum *et al.*, 2000, Zhou & Dexter, 1998]. Therefore, we test the data for normality and lognormality. We use two graphical (i.e. histograms and Q-Q plots) and one analytical way (i.e. Kolmogorov-Smirnov test) to test the data against the two hypothesized distributions.

Histograms

The first step in our analysis is constructing histograms of the total surgery duration. Figure 9 shows the histogram of the total surgery duration for specialty General Surgery.

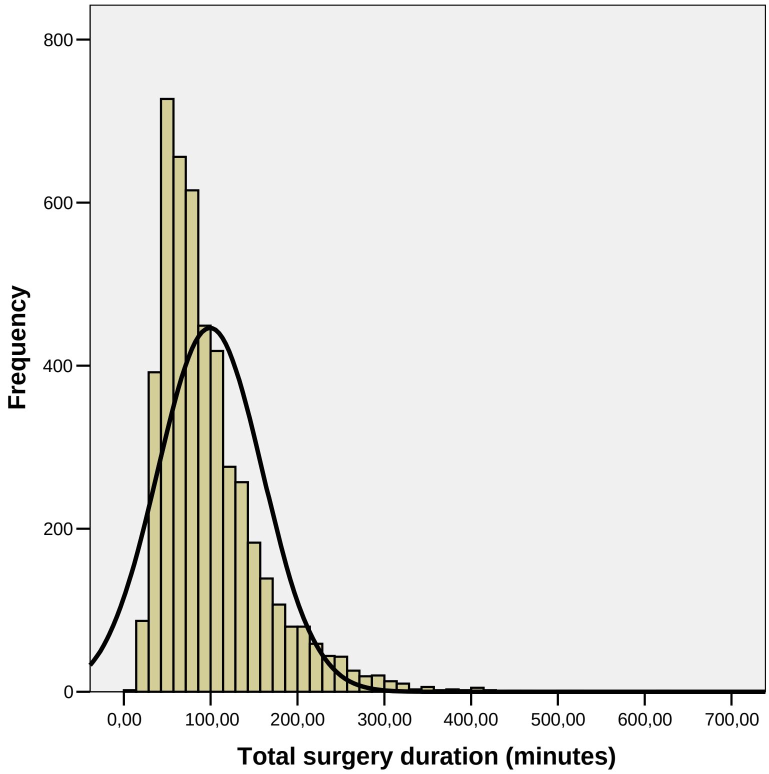

Figure 9: Histogram of the total surgery duration of 4.730 surgeries performed by General Surgery

To determine the distribution type of the surgery duration, we want to compare the surgery durations with a normal and a lognormal distribution. To do this, we first determine the mean and standard deviation of the surgery durations. In the histogram of the total surgery duration (Figure 9) we superimpose the curve of the normal distribution with the mean and standard deviation we calculated from the surgeries in the dataset. There is no good fit between the data and the normal curve, so we conclude the normal distribution is not a correct distribution to describe the data. The histogram further shows the data are skewed to the right. This is an indication of a lognormal distribution. The histograms of the other specialties are in Appendix B, and show the same deviation from the normal curve.

To continue our analysis, we construct a histogram of the logarithms of the total duration of the surgeries. We present this histogram in Figure 10.

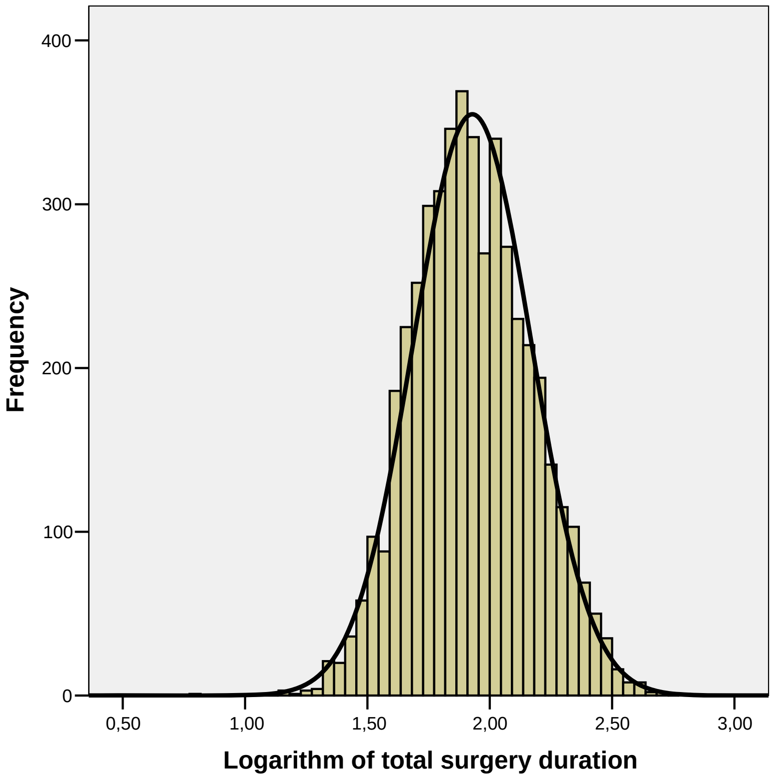

Figure 10: Histogram of the logarithm of the total surgery duration of 4,730 surgeries performed by General Surgery

Figure 10 shows a better fit between the data and the normal curve. This supports our hypothesis that the data are lognormally distributed. The histograms for the other specialties are given in Appendix C and show the same tight fit with the normal curve.

Q-Q plots

A second graphical way to test the data for lognormality is to construct Q-Q plots. To construct a Q-Q plot, the variable's distribution (total surgery duration in our case) is divided into quantiles (i.e. equal sized groups). Then these quantiles are plotted against the quantiles of the test distribution (normal or lognormal distribution in our case). If the points of the plot are clustered around a straight line, this indicates a match between the variable and the test distribution. Figure 11 shows the Q-Q plot for specialty General Surgery.

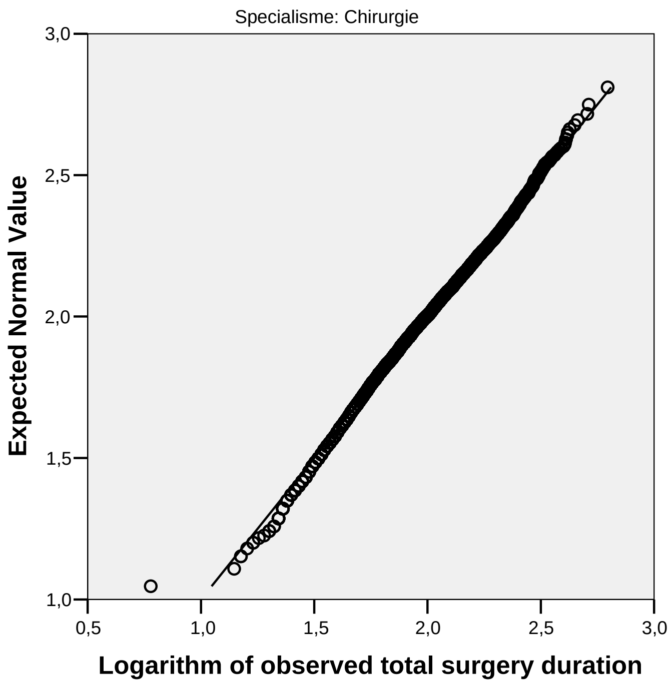

Figure 11: Q-Q plot of the logarithm of total surgery duration for specialty General Surgery

The clustering of the data points around the straight $y = x$ curve indicates a match between the observed data and the hypothesized lognormal distribution. The Q-Q plots of each specialty are given in Appendix D. All Q-Q plots indicate a good fit between the observed data and the hypothesized lognormal distribution.

Kolmogorov-Smirnov test

To confirm the lognormal distribution of the data, we perform a Kolmogorov-Smirnov test. This tests the null-hypothesis $H_0 : F = F_0$ against the alternative $H_1 : F \neq F_0$ where F is the unknown distribution function of our data, and F_0 is the given distribution function we expect we can describe our data with. In our case F_0 is the lognormal distribution with mean and variance calculated from our data. To test for lognormality, we may test the logarithms of the data against the normal distribution. The K.-S. test calculates the asymptotic Sigma value. Sigma represents the chance we falsely reject H_0. This means we accept H_0 at a (1-α)*100% confidence level if Sigma is larger than α. The K.-S. test for normality can be performed with almost any sample size. However, due to the nature of the test, for extremely large sample sizes the test is almost certain to reject H_0. This is because the test bases its result on the largest deviation from the hypothesized distribution. In extremely large datasets, a deviation large enough to base rejection of H_0 on can almost always be found [Dickinson 1976]. Table 20 shows the results of the test for specialty General Surgery.

Table 20. Results of the K.-S. test for lognormality of the total surgery duration of 4.730 surgeries performed by surgical specialty General Surgery

	Logarithm of Total Surgery Duration
Number of Surgeries	4,730
Mean	1.9286
Standard Deviation	0.24167
Asymptotic Sigma (2-tailed)	0.009

The results of the test for each specialty are presented in Appendix E. The value we need to evaluate the fit between a lognormal distribution and our data is the Sigma on the last row of the table. For General Surgery, this Sigma is 0.009. For a 95% confidence level, we use $\alpha = 0.05$. As Sigma is smaller than α, we reject H_0: the lognormal distribution does not appear to describe the data. The same conclusion can be drawn for the specialties Gynecology, Neurosurgery and Plastic Surgery. For the specialties Children's Surgery and Orthopedic Surgery however, Sigma>α. So for these specialties, we can immediately conclude the data can be described by a lognormal distribution with parameters determined by the observed data. Now let's take a further look at the tables of the tests resulting in a small value of Sigma.

The specialties for which the K.-S. test result in a Sigma smaller than alpha were the tests performed on surgeries of specialties with a large number of surgeries: more than 1,900 and up to 4,700 surgeries in the tested datasets. The tests performed on surgeries of specialties with a smaller number of surgeries (i.e. 150 and 81 surgeries in the respective datasets) resulted in larger values of Sigma. We assume the rejection of H_0 for the large datasets is caused by the size of the dataset rather than by non normality of the data. We check this by dividing the large datasets into smaller subsets. For example for surgical specialty General Surgery, we split the dataset into subsets based on the OR the surgeries are performed in and the day of the week the surgery is performed (e.g. all surgeries performed in OR 4 on all Wednesdays in the dataset are in one subset). This resulted in subsets with 3 to 331 surgeries per subset. K.-S. tests performed on all these subsets indicate they can be described by lognormal distributions. Therefore, we conclude the rejection of H_0 for the larger datasets was caused by the large number of surgeries in the datasets. Thus we conclude the total surgery duration for the six specialties we consider in this research is lognormally distributed.

A3.2 Determining the descriptives of the data

In Appendix A3.1 we determined the distribution type to describe the total surgery duration. We calculate the two descriptives for this distribution type: the mean and the standard deviation. We determine these descriptives for each of the six specialties we included in the analysis. Table 21 presents the results of this analysis.

Table 21. Mean and standard deviation of the total surgery duration for the six largest surgical specialties

	Number of procedures (%)	Mean (minutes)	Standard deviation (minutes)
General Surgery	42	99	60
Gynecology	21	77	42
Children's Surgery	1	30	14
Neurosurgery	18	110	72
Orthopedic Surgery	1	114	70
Plastic Surgery	17	94	83

A4 Conclusion of the data analysis

We have determined which data to base our analysis on in Appendix A1. Then we performed a statistical outlier analysis to determine the validity of the data and the percentage of the total number of surgeries each specialty performs in Appendix A2. Finally, we determined the type of statistical distribution in Appendix A3.1 and the descriptives of these distributions in Appendix A3.2).

Appendix B: Histograms of total surgery duration

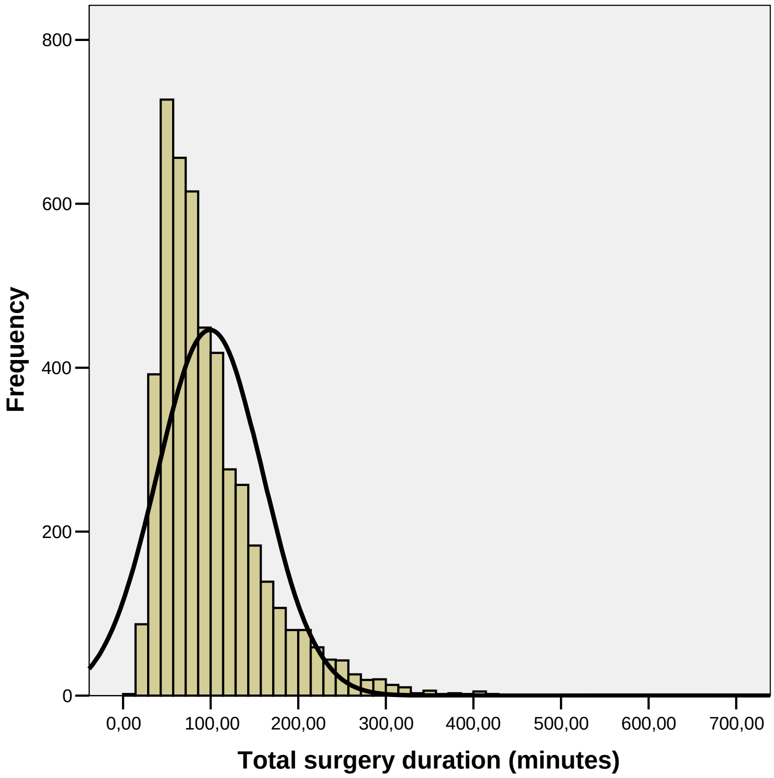

Figure 12: Histogram of total surgery duration for 4,730 surgeries of specialty General Surgery

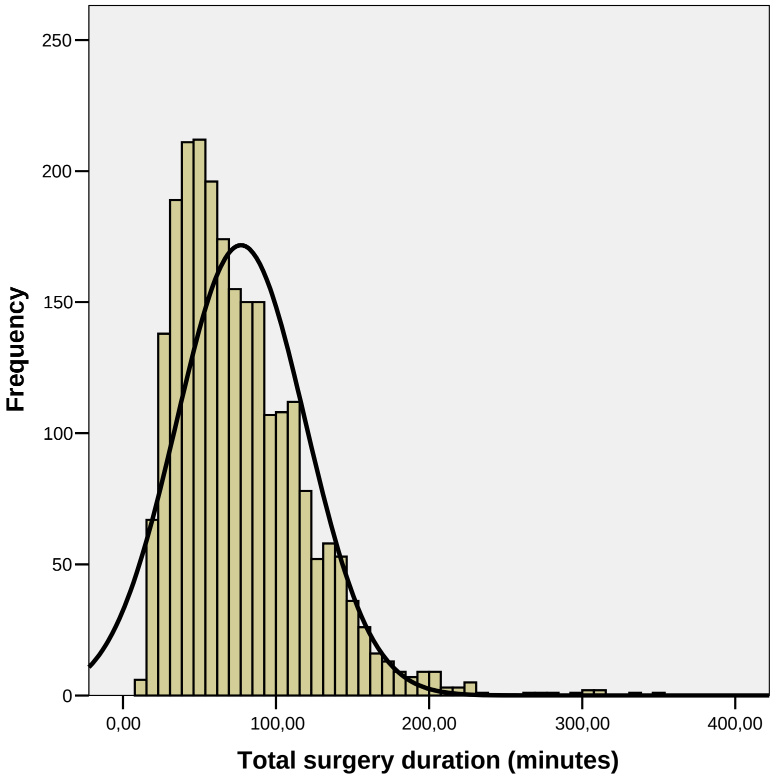

Figure 13: Histogram of total surgery duration for 2,363 surgeries of specialty Gynecology

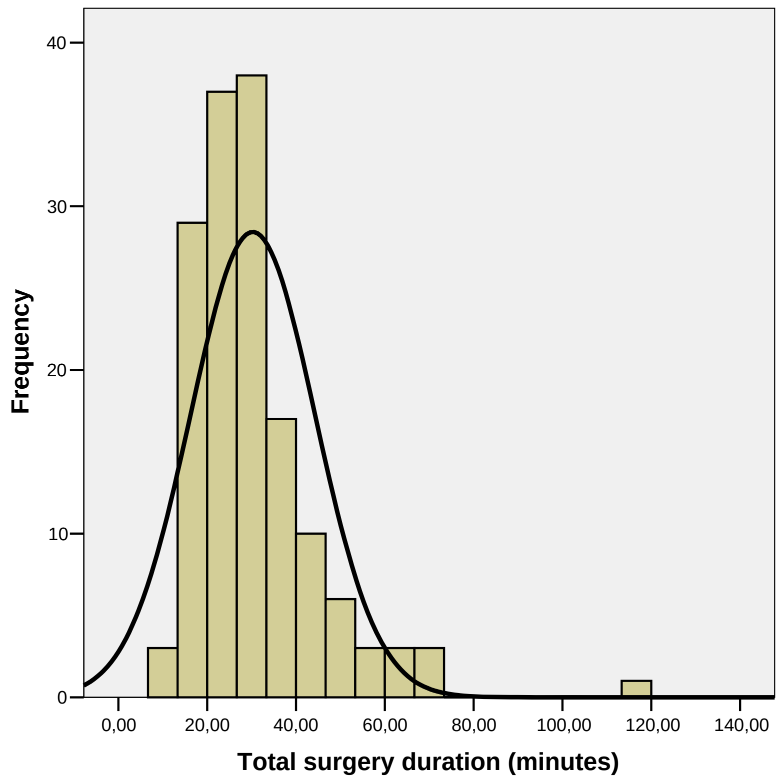

Figure 14: Histogram of total surgery duration for 150 surgeries of specialty Children's Surgery

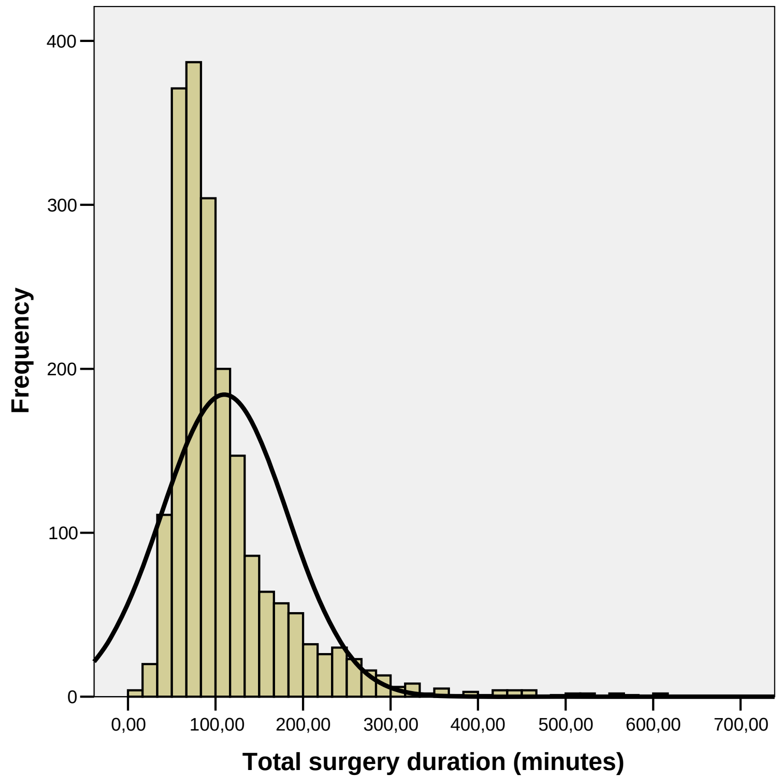

Figure 15: Histogram of total surgery duration for 1,990 surgeries of specialty Neurosurgery

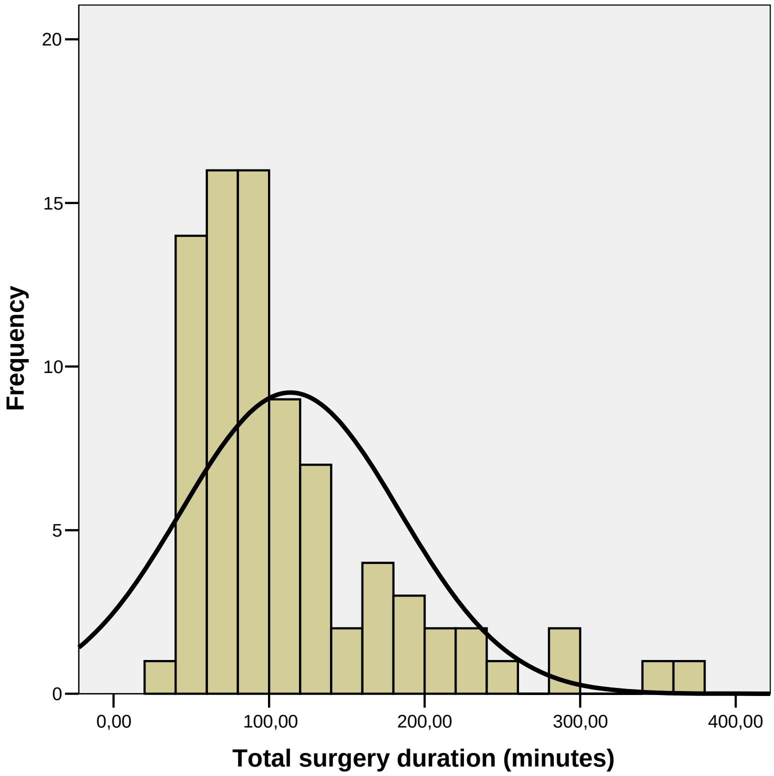

Figure 16: Histogram of total surgery duration for 81 surgeries of specialty Orthopedic Surgery

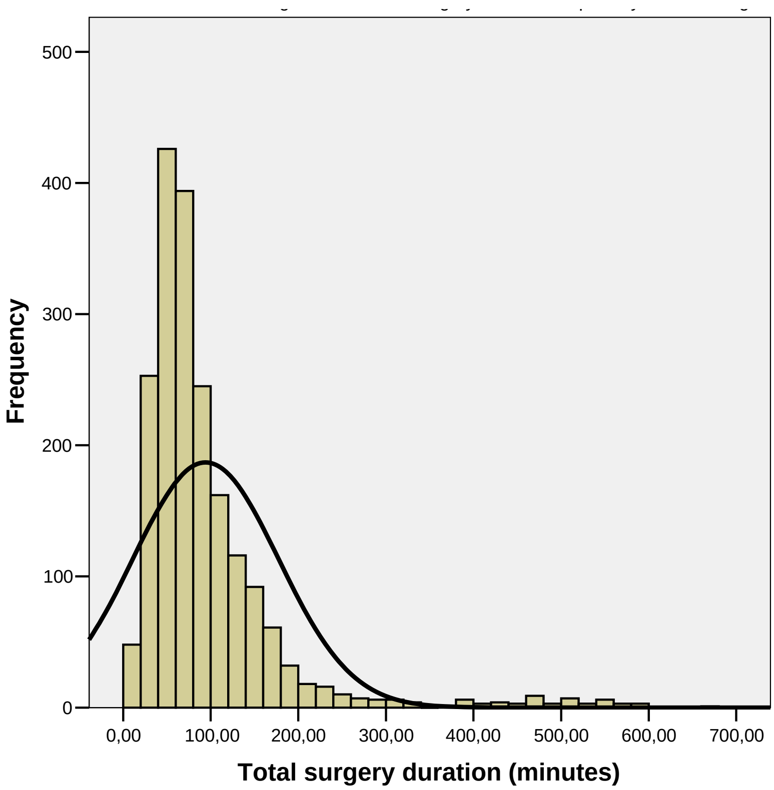

Figure 17: Histogram of total surgery duration for 1,948 surgeries of specialty Plastic Surgery

Appendix C: Histograms of the logarithms of total surgery duration

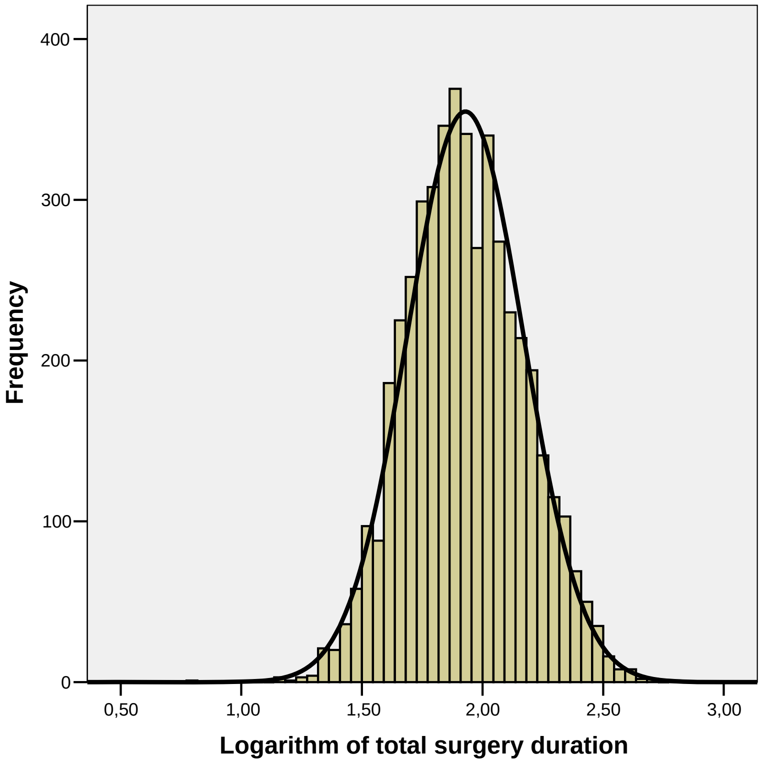

Figure 18: Histogram of the logarithm of the duration for 4,730 surgeries of specialty General Surgery

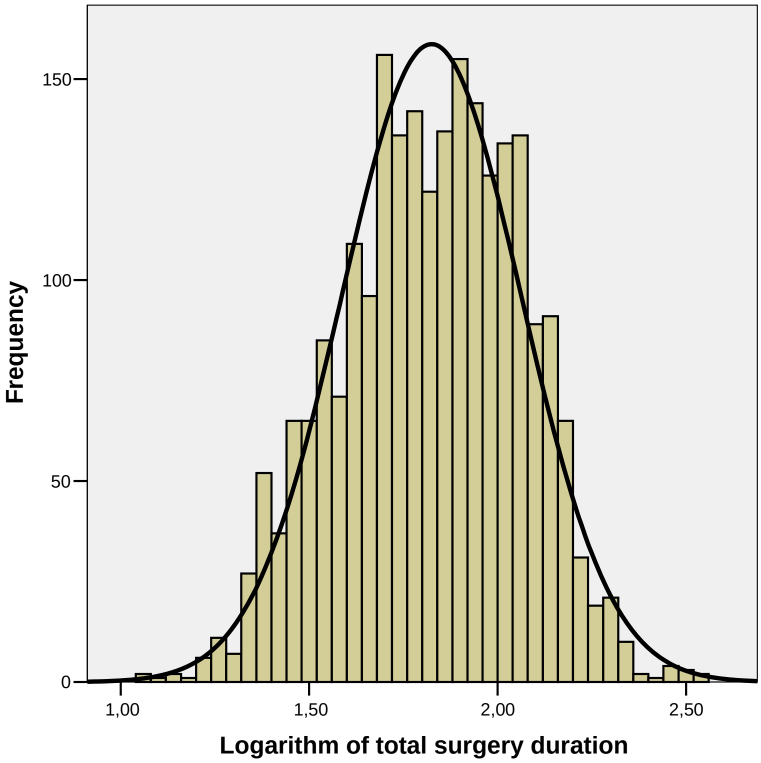

Figure 19: Histogram of the logarithm of the duration for 2,363 surgeries of specialty Gynecology

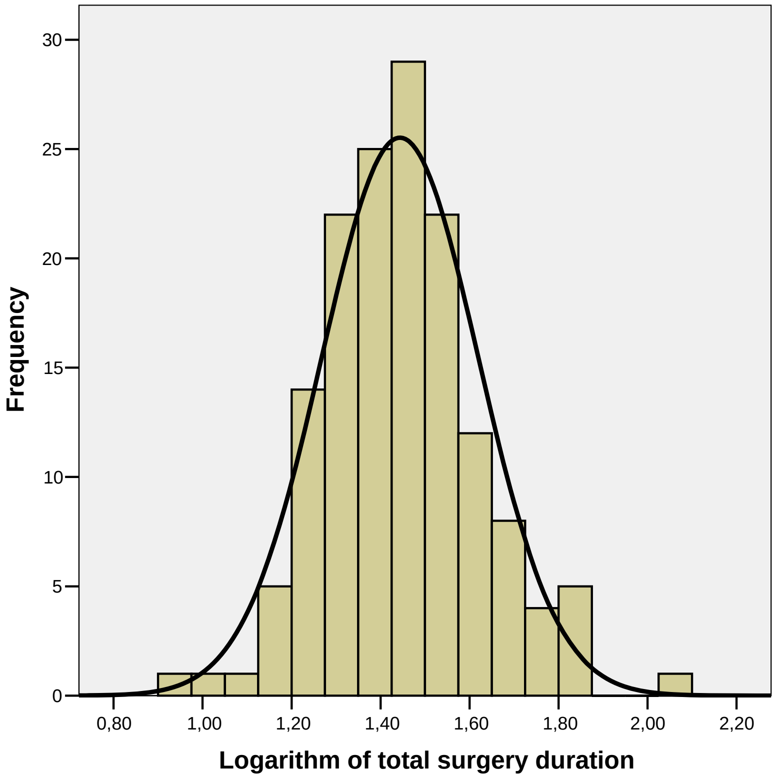

Figure 20: Histogram of the logarithm of the duration for 150 surgeries of specialty Children's Surgery

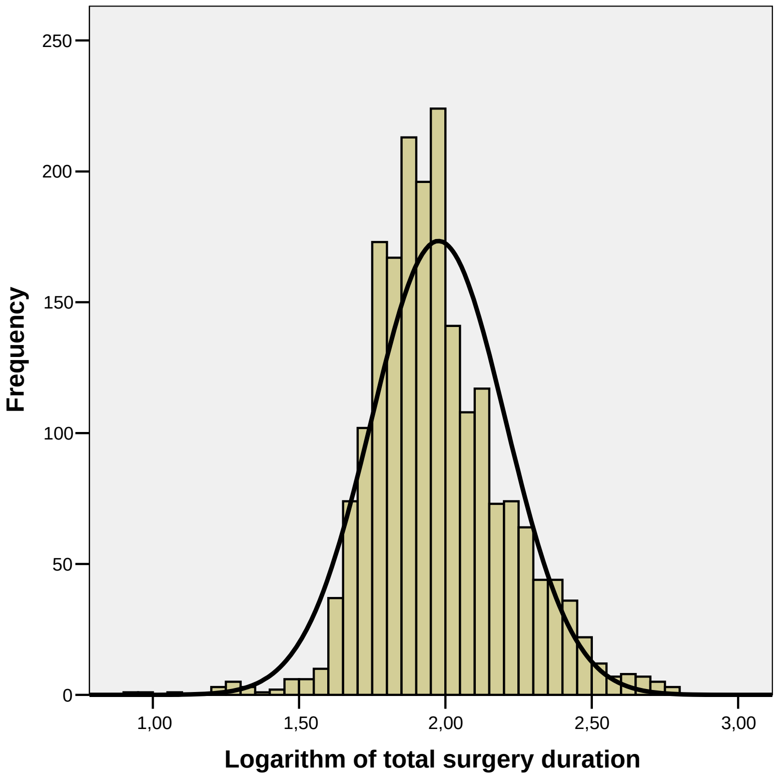

Figure 21: Histogram of the logarithm of the duration for 1,990 surgeries of specialty Neurosurgery

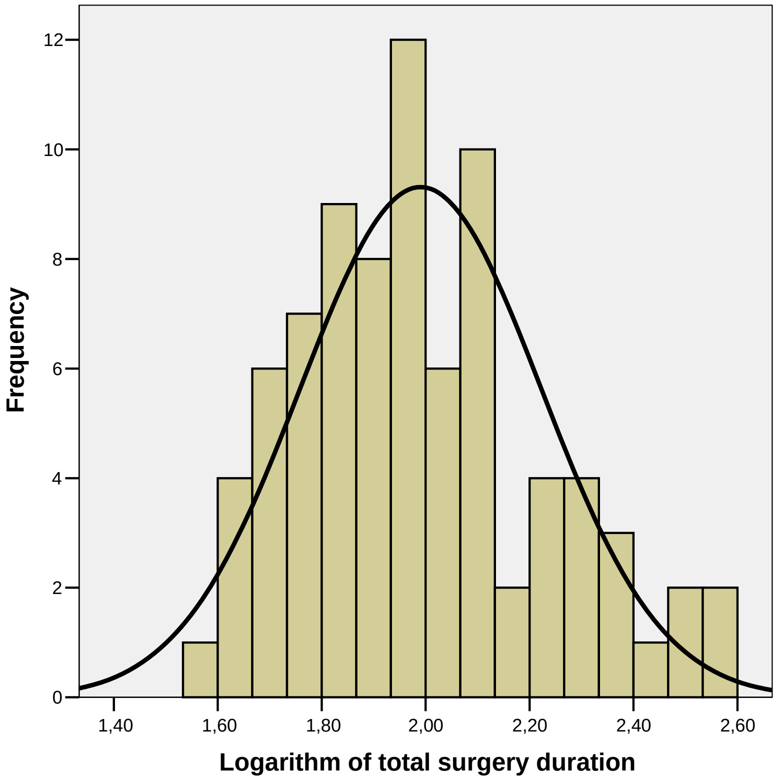

Figure 22: Histogram of the logarithm of the duration for 2,363 surgeries of specialty Gynecology

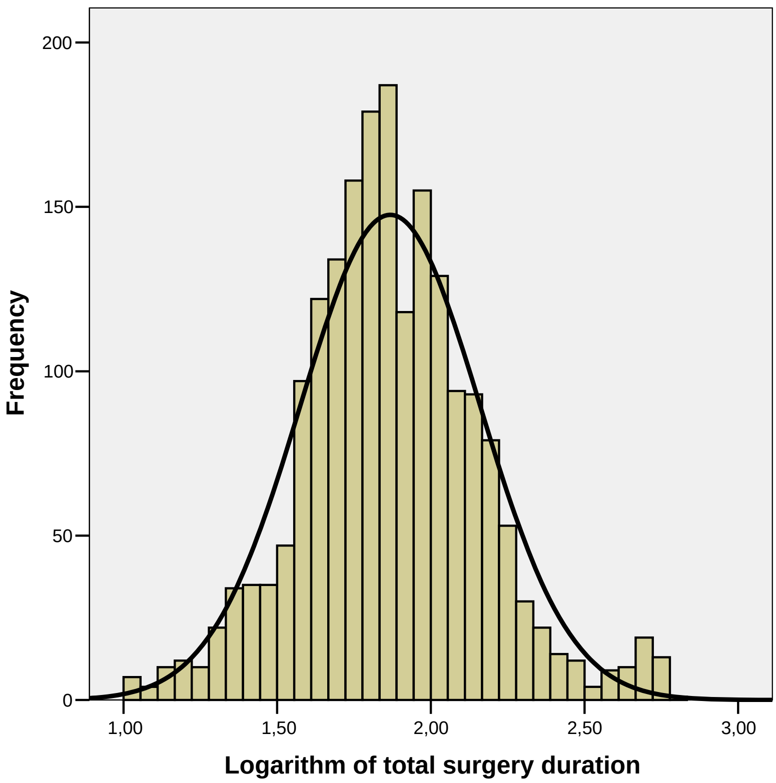

Figure 23: Histogram of the logarithm of the duration for 1,948 surgeries of specialty Plastic Surgery

Appendix D: Q-Q plots

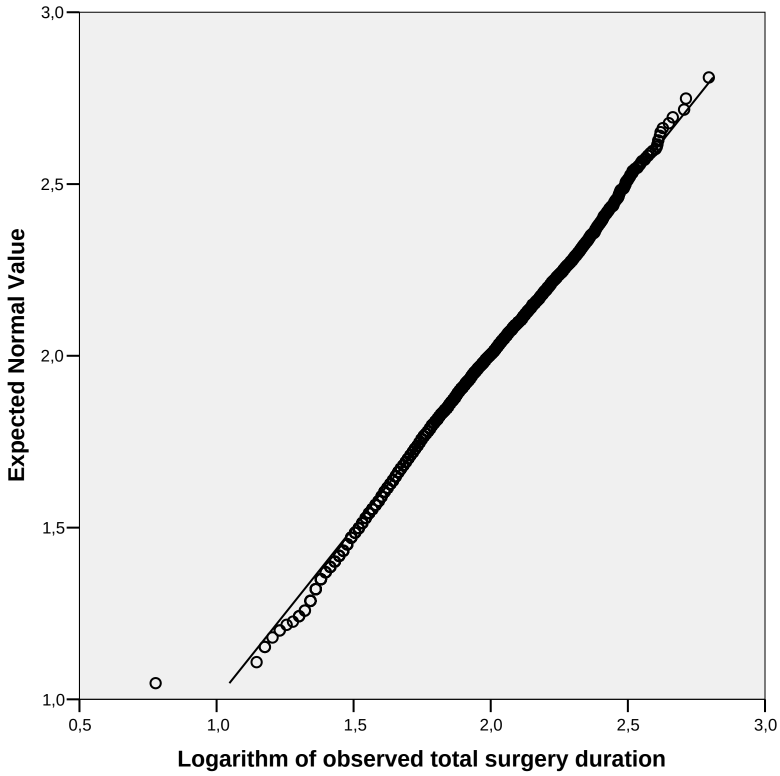

Figure 24: Q-Q plot of the logarithm of the total surgery duration (specialty General Surgery)

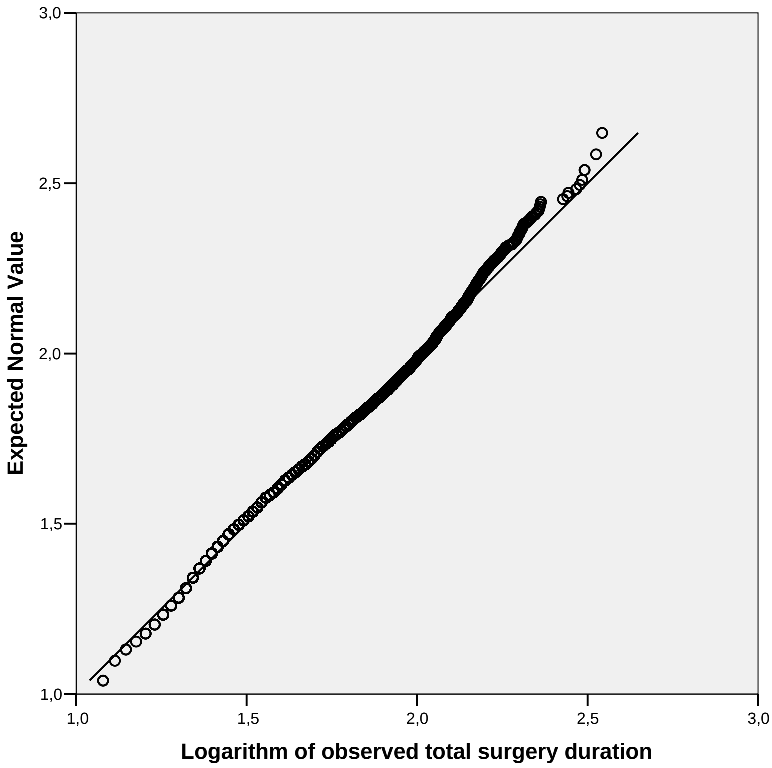

Figure 25: Q-Q plot of the logarithm of the total surgery duration (specialty Gynecology)

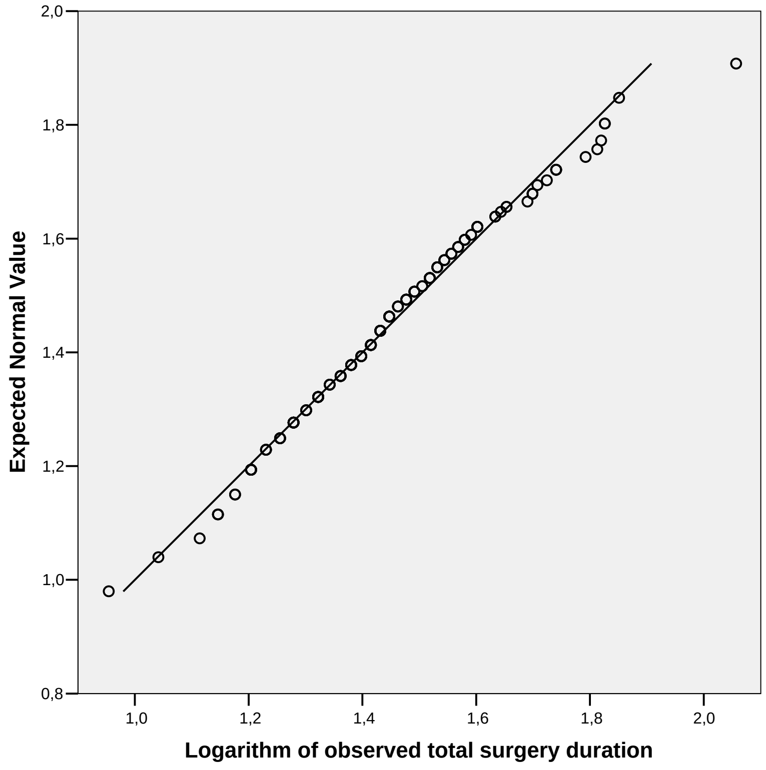

Figure 26: Q-Q plot of the logarithm of the total surgery duration (specialty Children's Surgery)

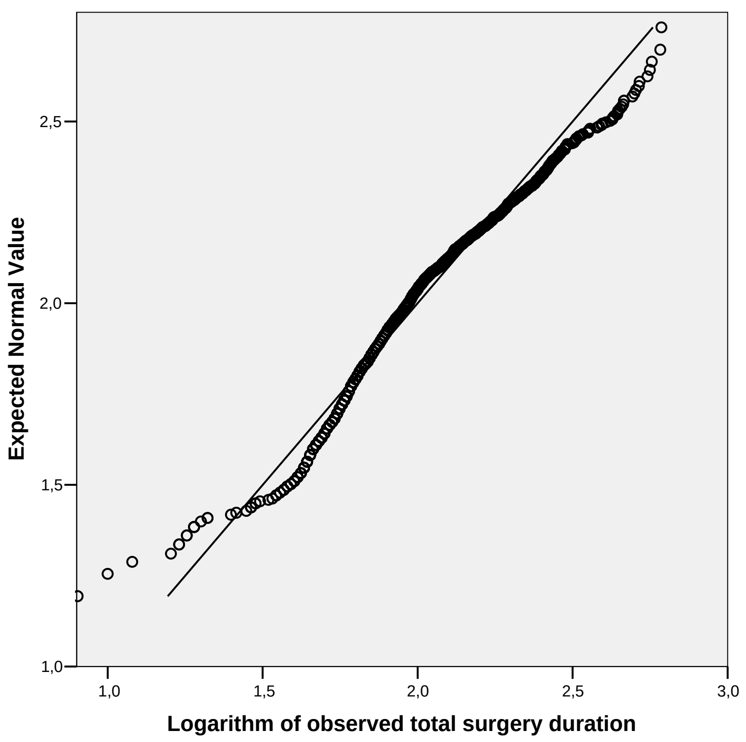

Figure 27: Q-Q plot of the logarithm of the total surgery duration (specialty Neurosurgery)

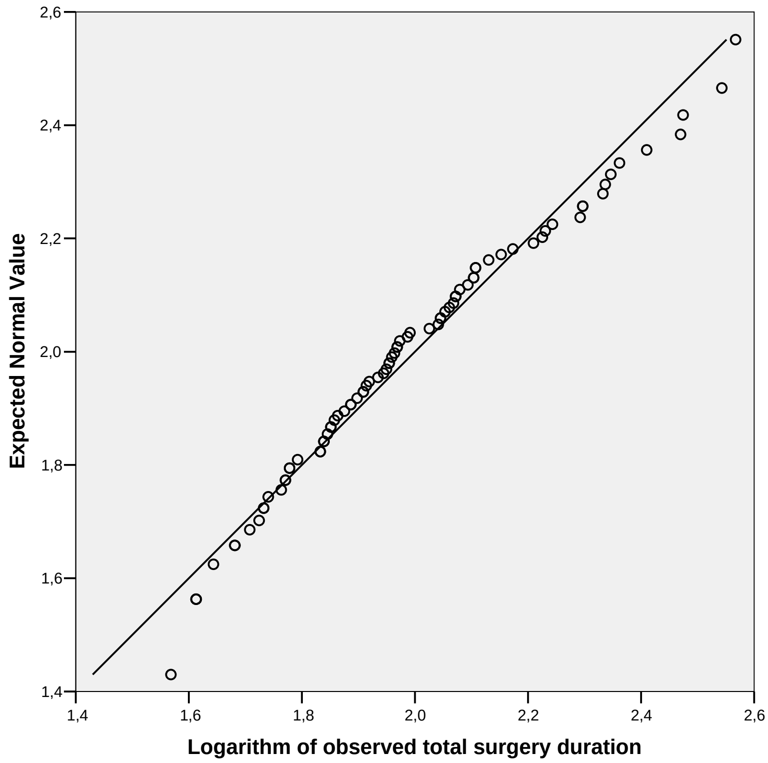

Figure 28: Q-Q plot of the logarithm of the total surgery duration (specialty Orthopedic Surgery)

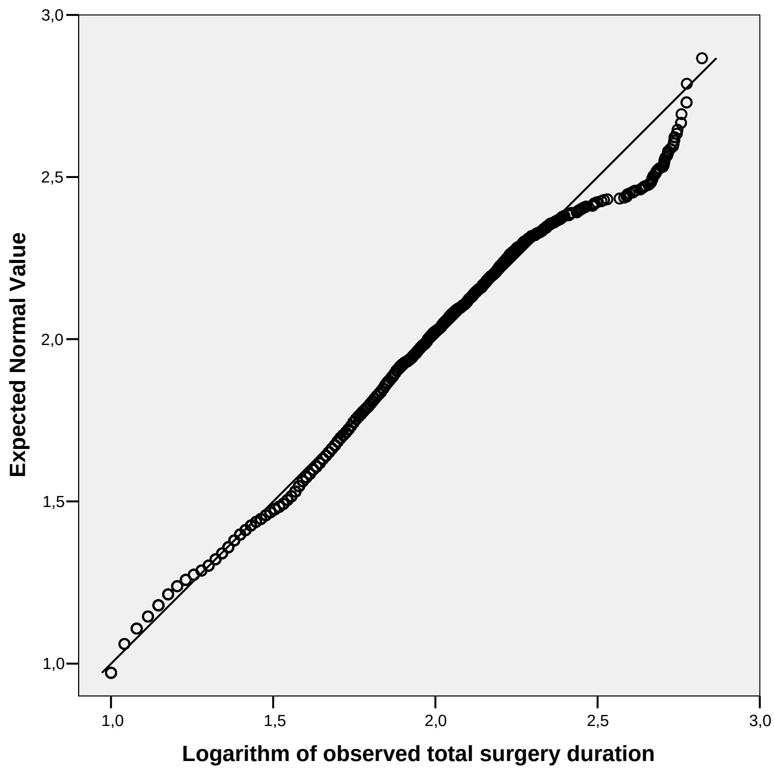

Figure 29: Q-Q plot of the logarithm of the total surgery duration (specialty Plastic Surgery)

Appendix E: Results of the Kolmogorov-Smirnov tests

Table 22. Results for the Kolmogorov-Smirnov test for lognormality of the total surgery duration

	Number of surgeries	Mean	Standard deviation	Sigma
General Surgery	7,430	1.9286	0.24167	0.009
Gynecology	2,363	1.8246	0.23758	0.003
Children’s Surgery	150	1.4438	0.17587	0.537
Neurosurgery	1,990	1.9762	0.22889	0.000
Orthopedic Surgery	81	1.9904	0.23136	0.596
Plastic Surgery	1,948	1.8678	0.29252	0.008

Appendix F: Descriptions of semi-urgent surgeries

As we want to simulate the effect of semi-urgent surgeries arriving and claiming resources, we need the expected number of semi-urgent surgeries per day, the expected surgery duration, the standard deviation of the surgery duration and the type of statistical distribution. In this appendix, we analyze the 6,033 semi-urgent surgeries that have been registered at location SZ of hospital Isala klinieken during the period 01-01-2006 through 23-07-2007. Analogous to the methods of Appendix A, we first determine the distribution type, and then we determine the descriptive of the semi-urgent surgeries.

As we expect the surgery duration to have the same distribution type as the elective surgeries (i.e. we hypothesize the surgery durations are lognormally distributed), we start by constructing histograms of the logarithm of the surgery durations. Figure 30 shows the histogram of the logarithm of the total surgery duration of the 6,033 registered semi-urgent surgeries and the curve of the normal distribution with mean and standard deviation of the data.

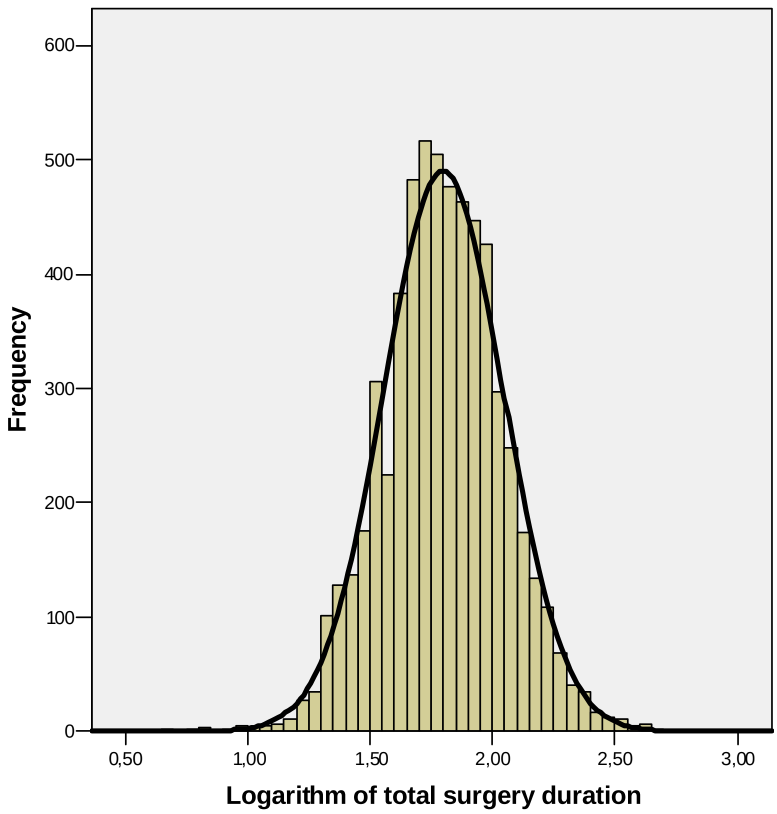

Figure 30: Histogram of the logarithm of the total surgery duration of 6,033 semi-urgent surgeries

The good fit between the data and the curve of the normal distribution with the mean and standard deviation calculated from the semi-urgent surgeries in the dataset is an indication the emergency surgery durations are lognormally distributed. Therefore, we continue testing the data for lognormality. The next visual test we perform is constructing a Q-Q plot of the surgery durations. Figure 31 presents this plot.

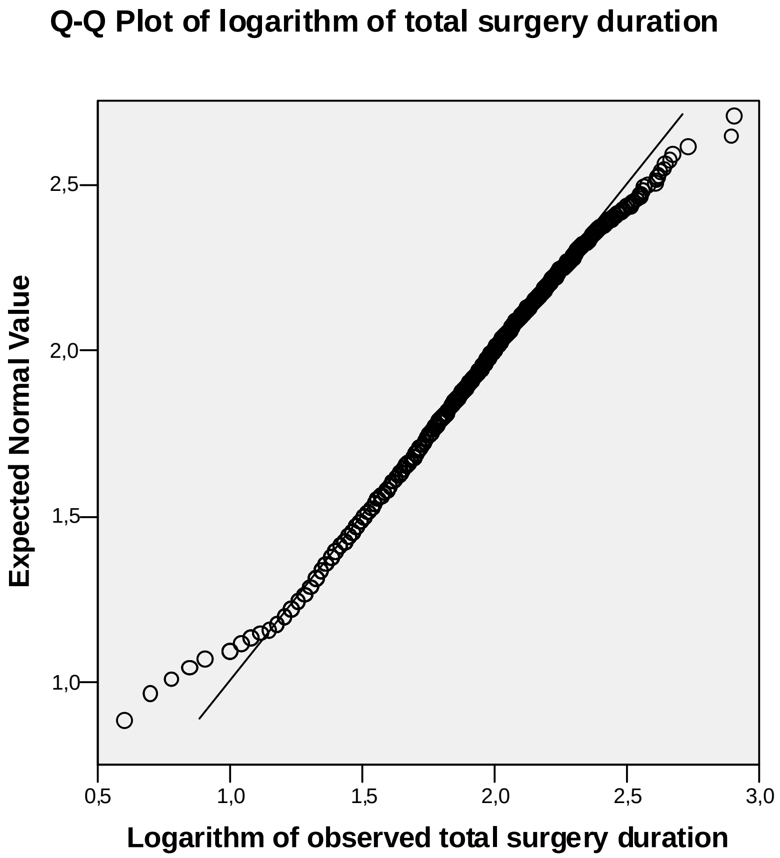

Figure 31: Q-Q plot of the logarithm of total surgery duration for 6,033 semi-urgent surgeries

All data points cluster around the straight $y = x$ line. This indicates a match between the data and the expected lognormal distribution.

To confirm the lognormal distribution, we perform a Kolmogorov-Smirnov test on the emergency surgery durations. As the dataset contains over 6000 surgeries, we first take a smaller sample from the dataset, as argued in Appendix A3.1. We randomly select 200 surgeries, and perform the K.-S. test on these surgeries. Table 23 presents the results of this test.

Table 23. Results of the K.-S. test for lognormality of the surgery duration of 200 semi-urgent surgeries

	Logarithm of Total Surgery Duration
Mean	1.8093
Standard Deviation	0.26250
Asymptotic Sigma (2-tailed)	0.888

We accept the hypothesis at a (1-α)*100% confidence level, if Sigma is larger than α. Therefore, we conclude at a 95% confidence level, the surgery durations are lognormally distributed.

To determine the length of the semi-urgent surgeries in the discrete event simulations, we calculate the mean and standard deviation of the 6033 emergencies surgeries. Table 24 gives the results of these calculations.

Table 24. Descriptives of 6,033 semi-urgent surgeries

	Mean (minutes)	Standard deviation (minutes)
Semi-urgent surgeries	74.09	48.30

Appendix G: Recommendations for Isala klinieken

Management of the OR department of Isala klinieken in Zwolle initiated this research to increase the efficiency of the OR department. We developed surgery scheduling algorithms that increase efficiency of the operating theatre by reducing the waiting time between surgeries. In this appendix, we give additional recommendations concerning the OR department.

The sensitivity analyses in Section 5.4 show that the proposed algorithms perform better when more accurate surgery data are used to create the surgery schedule. Therefore, we recommend further research to focus on storing and retrieving surgery data such that they can be used to accurately predict surgery duration.

Performing a certain surgical procedure can be restricted to a specific day in the week due to availability of surgeons. These restrictions limit the surgery planner in his possibilities to adjust the surgery schedule. Therefore, we recommend further research to focus on practical constraints to the surgery schedule, such as surgeon availability and IC bed capacity.

This research focused on physical resources, that are in use only during the surgery. There are many more resources in use only during the surgery, including personnel, and other physical resources such as heart-lung machines and IV-pumps. The proposed solution methods are generic and can be applied to any of these resources. However, the algorithms optimize the surgery schedule based on one resource. Further research should therefore focus on adjusting the algorithms such that they can include multiple resources.

The results of applying Algorithm 2 and Algorithm 4 include a reduction from 4.0 to 0.8 minutes average waiting time per surgery, and a reduction from 276 to 246 minutes average overtime per day. The average of 29 surgeries per day (7500 surgeries in 260 days) results in 93 minutes waiting time reduction per day. The overtime is reduced by 30 minutes per day. The remaining reduction in waiting time does not directly decrease the amount of overtime. However, still 246 minutes of overtime per day remain. Part of this overtime is caused by the variability in the surgery duration. The exact causes of the remaining overtime are subject of further research. Also, dealing with the fluctuations in personnel requirements resulting from variations in overtime are subject of further research.