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OPERATING ROOM PLANNING AND SCHEDULING:

SOLVING A SURGICAL CASE SEQUENCING PROBLEM

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Brecht Cardoen
Leuven, 23 januari 2009

Abstract

This dissertation aims at the study of operating room planning and scheduling problems that arise in a hospital setting. While planning can be seen as the reconciliation of supply and demand, scheduling points at the construction of a detailed timetable that shows at what time or date activities, i.e. surgeries, should start and when they should end. Since these decisions have many repercussions throughout the entire hospital, it is worthwhile to put effort in their optimization through the application of techniques that stem from the domain of operations management and operations research.

The text of the dissertation is organized as follows. **Chapter 1** deals with the importance of health care services in today's society and illustrates the major role that hospitals, and in particular their operating rooms, play in the delivery of these services. Since there is an increasing importance of ambulatory surgery or day surgery, we study the operating room planning and scheduling problems mainly from an outpatient perspective. **Chapter 2** provides a detailed and structured literature review that covers the recent developments in operating room planning and scheduling. We discuss scientific contributions that appeared in or after 2000 as long as their focus is restricted to operating room planning or surgery scheduling, as explained in the first paragraph of this abstract. One of the findings that appears from the literature review is the lack of a clear and consistent scheme to classify the contributions on operating room planning and scheduling. This results, amongst other, in the ambiguous use of terminology and unclear problem descriptions. Therefore, we propose in **Chapter 3** a concise classification scheme, based on the organization of the literature review of Chapter 2,

to classify operating room planning and scheduling problems. This way we hope to provide some guidance and clarity in future scientific research. In **Chapter 4** we examine the current state of operating theater planning and scheduling in Flanders (Belgium). Results of 52 respondents who answered the electronic questionnaire, are summarized. These results both relate to the development of the surgery schedule and its realization in practice. **Chapter 5** constitutes the main chapter of this dissertation. We introduce a scheduling problem in which we have to sequence surgeries within the operating rooms of a freestanding ambulatory day-care center. The sequencing problem at hand originated from the UZ leuven, which is the academic hospital of the Katholieke Universiteit Leuven. Next to a detailed problem description, the chapter features multiple solution approaches to solve the daily sequencing problem. While most of the approaches are mixed integer linear programming based, we also describe a dedicated branch-and-bound approach. We provide computational results of the solution procedures using an artificial test set that was generated using both real and expert data. Although the algorithmic approaches satisfy their goal and hence produce optimized surgery schedules, they are not user-friendly and hard to modify when used in practice. Therefore, we developed in **Chapter 6** a graphical user interface that substantially facilitates the use of the algorithms with respect to the input of data, the output of results and the flexibility to change settings. The introduction of such a visual shell clearly enhances the end-user's ability to evaluate various schedules and gain insights that are otherwise hard to capture. In addition to the presentation of this interface, we report on its application at the day-care center of the UZ Leuven Campus Gasthuisberg. The dissertation concludes with **Chapter 7**, which summarizes the major issues that were addressed in all preceding chapters. Furthermore, directions for future research on operating room planning and scheduling are provided.

Samenvatting

In dit proefschrift bestuderen we planningsproblemen die zich manifesteren in het operatiekwartier van ziekenhuizen. Planning doelt niet alleen op de afstemming van vraag en aanbod, maar duidt ook op het opstellen van een gedetailleerd tijdschema dat aangeeft wanneer activiteiten, in dit geval operaties, zouden moeten starten en wanneer ze zouden moeten worden beëindigd. Aangezien de gevolgen van deze beslissingen voelbaar zijn doorheen het volledige ziekenhuis, lijkt het aangewezen dit beslissingsproces te optimaliseren en enkele technieken uit het domein van het operationeel onderzoek toe te passen en uit te werken.

We kunnen de tekst van het proefschrift als volgt opdelen. In **Hoofdstuk 1** wordt het belang van de gezondheidszorg in onze hedendaagse maatschappij onderstreept en tonen we aan hoe ziekenhuizen, en in het bijzonder hun operatiekwartier, een vooraanstaande rol spelen in het toedienen van de zorg. Het toenemende belang van dagchirurgie leidt ons ertoe om voornamelijk vanuit dit perspectief de planningsproblemen in het operatiekwartier te benaderen. **Hoofdstuk 2** bestudeert op een gedetailleerde en gestructureerde wijze de recente wetenschappelijke literatuur die verschenen is over operatieplanning (verschenen na 2000). Eén van de conclusies die volgen uit dit literatuuronderzoek is het gebrek aan een consistent classificatieschema om operatieplanningsproblemen te omschrijven. Dit resulteert in ondermeer een ambigu gebruik van terminologie en onduidelijke probleemformuleringen. Daarom wordt in **Hoofdstuk 3** een classificatieschema voorgesteld, gebaseerd op de structuur van het literatuuroverzicht van Hoofdstuk 2, met als doel de probleemformuleringen van toekomstig onderzoek binnen dit domein

te verduidelijken. In **Hoofdstuk 4** bestuderen we de huidige operatieplanningspraktijken van de ziekenhuizen in Vlaanderen (België) en vatten we de antwoorden van 52 respondenten samen die de elektronische vragenlijst hebben ingevuld. De resultaten hebben betrekking op zowel het opstellen van de operatieplanning als de uiteindelijke realisatie van de vooropgestelde planning. **Hoofdstuk 5** introduceert een planningsprobleem dat aangereikt werd door de UZ Leuven, het universitair ziekenhuis van de Katholieke Universiteit Leuven. Het probleem bestaat uit het bepalen van de volgorde van operaties in de operatiezalen van het chirurgisch dagcentrum. Naast een gedetailleerde probleemformulering beschrijft het hoofdstuk verschillende procedures om dit dagelijkse operationeel probleem op te lossen en het beslissingsproces van de planner te ondersteunen. Hoewel de meeste procedures gebaseerd zijn op lineaire programmering, wordt ook een branch-and-bound procedure voorgesteld. We maken gebruik van een artificiële testset, gebaseerd op kwantitatieve data en informatie aangereikt door de planner op basis van ervaring, om de rekenkundige capaciteiten van de procedures te testen. Hoewel de algoritmes performant blijken en bijgevolg geoptimaliseerde operatieschema's aanreiken, kunnen er nog verbeteringen aangebracht worden in het gebruiksgemak en de bijhorende flexibiliteit. Daarom wordt in **Hoofdstuk 6** een grafische ondersteuning ontwikkeld die het gebruiksgemak wat betreft het invoeren van de gegevens, de interpretatie van de uiteindelijke resultaten en de flexibiliteit inzake het aanpassen van parameters significant verbetert. De grafische component verhoogt de mogelijkheid voor de eindgebruiker van het programma om verschillende operatieschema's te vergelijken en inzichten te verwerven die anders niet kunnen waargenomen worden. Naast de visualisatie zelf rapporteren we in Hoofdstuk 6 ook over de feitelijke toepassing van de applicatie in het chirurgisch dagcentrum van de UZ Leuven Campus Gasthuisberg. Het proefschrift wordt afgerond met **Hoofdstuk 7** waarin de belangrijkste bevindingen van de voorgaande hoofdstukken worden samengevat en waarin enkele suggesties worden aangereikt om het onderzoek rond operatieplanning in de toekomst verder te zetten.

Contents

Chapter 1

Introduction

The increased pace of change that characterizes today's society has a major impact on the management strategies applied to business processes. Nowadays, the era of mass production, which is merely process-oriented and focused on financial costs, seems to be repressed by strategies that address flexibility and agility [84]. The primary objective now is to simultaneously improve costs, quality and time aspects and relate these issues to both the process and the customers. Since these outputs largely depend on the accuracy by which operations management techniques are applied, various planning and scheduling problems have been studied by the scientific community. Although the resulting techniques and insights mostly relate to the industrial domains, such as machine scheduling or project scheduling, they also apply to the service sector. These services even tend to be more complex than their industrial counterparts, as they explicitly take human factors into account. In this introductory chapter, we emphasize the need for and the importance of operations management techniques applied to the provision of *health care* services. In a first section, we define the scope of the dissertation and indicate how the operating room planning and scheduling process relates to the larger health care context. A second section is consecutively added to outline the various chapters that are presented in this dissertation.

1.1 Motivation

Many indicators, which are frequently expressed in financial terms, can be identified to illustrate the importance of services in today's society. One major indicator is, for instance, the public and private education expenditure, which covers expenditure on schools, universities and other public and private institutions involved in delivering or supporting educational services. In 2004, countries that take part in the Organization for Economic Co-operation and Development (OECD) spent on average 6.2% of their gross domestic product (GDP) on public and private education [212]. Although this percentage is already elevated, health spending easily exceeds this share: in 2004 the share of health expenditure was on average 8.9% of the GDP amongst OECD countries [211].

Recently, the OECD has updated their statistics on health expenditure with data of 2006. Figure 1.1 provides a country-based visualization of these data, expressed again as a share of the GDP [213]. We notice that the percentage of expenditure related to health care (OECD average) equals the percentage that was obtained in 2004, namely 8.9%. This, however, does not imply that health expenses did not increase over the past few years. In fact, in 2006 health expenditure did exhibit a real annual growth rate of 3.1% for the OECD member countries [213]. It should be noted, though, that health expenditure is currently increasing at a decreasing pace. This evolution is visualized in Figure 1.2. The decreasing pace of the health expenses is in contrast to the growth rate of the GDP, which seems to increase at an increasing pace. Figure 1.2 furthermore shows that we are currently in a transition state. From 2004 on, it seems that the growth rate of the GDP exceeds the growth rate of the expenditure on health care. This implies that the share of health expenditure will decrease in the future if this trend holds. Nevertheless, the high amount of health spending, supported by the fact that there is still a significant positive growth rate, clearly indicates the economic importance of the health care services sector.

When we return to Figure 1.1, we furthermore see that the number of OECD members that exhibit a share that is less than 8.9% equals the number of

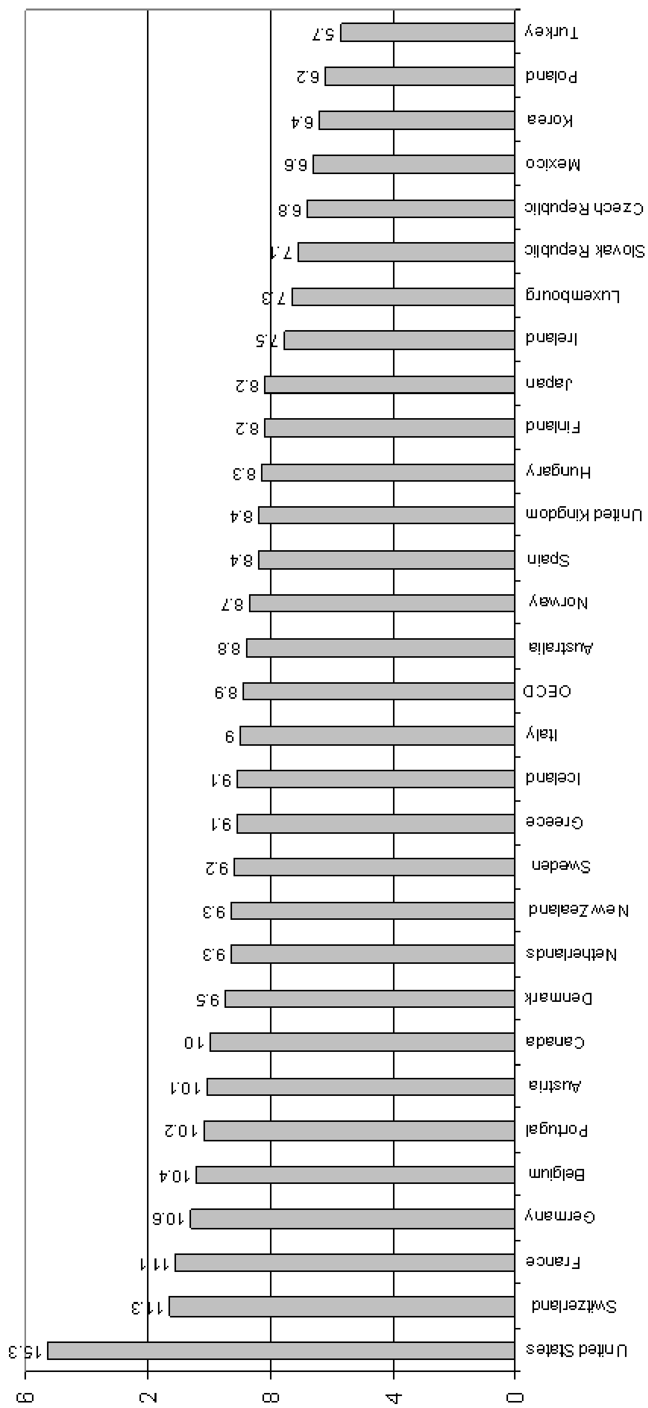

Figure 1.1: Health expenditure as a share of the GDP in 2006 ([213])

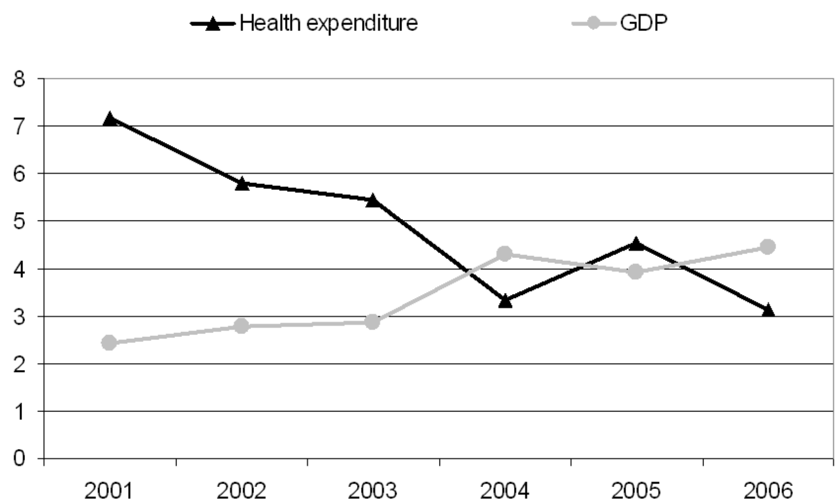

Figure 1.2: Real annual growth rates in health expenditure and GDP, OECD average, 2001 to 2006 ([210, 213])

members with a share that exceeds 8.9%. This implies that the OECD average, as a statistic, does not really suffer from skewness. However, it does not mean that the share of the countries among themselves is of comparable size. Belgium, for instance, clearly exceeds the average as it has a high share of 10.4%. Figure 1.1 also features one clear outlier, namely the United States (15.3%), which surpasses the shares of other countries by far. Many reasons can be found to explain the differences in health spending. Before we discuss some explanatory variables, however, it is interesting to know health spending's constituent components. Poisal et al. [230] recently disaggregated the health expenditure in the United States and studied to what extent the subcategories contribute to the total health spending. In particular, they divide their national health expenditure (NHE) in two main categories, namely the health services and supplies (94% of NHE) and investments (6% of NHE) such as research or structures and equipment (data of 2005). When we focus on the health services and supplies category, main cost drivers are related to the provision of personal health care. Especially hospital care (31% of NHE), physician and clinical services (21% of NHE), the prescription of drugs (10% of NHE) and nursing home care (6% of NHE) contribute to the high level of health expenditure. From these results, it turns out that hospitals and physicians are actually major drivers of health expenditure.

As mentioned, many variables can be identified in order to explain the differences in health spending. Below we list a limited number of potential determinants of health expenditure that are addressed and discussed in [155, 200]:

- *Demographics:* The most common demographic variable is the age of the population. The larger the proportion of elderly in the society, the larger we might expect health expenditure to be. Other variables are, amongst other, sex, race or ethnicity.
- *Insurance:* The spread of insurance should steadily reduce the price of health care to the consumer. This leads to an increased demand for medical services, thereby resulting in increased health spending.
- *Health status:* Variables related to the health status of people that might increase health expenditure are, amongst other, obesity, smoking, high cholesterol levels and chronic alcohol drinking.
- *Provider supply and organization:* This category embeds variables such as the number of hospital beds or the total number of physicians per capita. An important remark here relates to the occurrence of supplier-induced demand. This way, physicians want to protect their income by creating unnecessary medical demand for health services (such as requesting supplementary tests or revisions).
- *Economic variables:* The percentage of the population who live in poverty or the disposable real income are two examples of economic variables that might influence the health expenditure. Note that also inflation is an important explanatory factor when we are interested in the changes of health spending over time.
- *Medical technology:* This category covers variables such as the number of academic health centers, the percentage of hospitals with organ transplant capabilities or the percentage of hospitals with CT, MRI, PET or SPECT scanners. This category actually represents variables

that witness the increased capabilities of medicine, such as the development of new procedure types.

Up to now it seems difficult to estimate what variables really determine health expenditure and to what extent they have an impact. What we do know for sure, however, is that many variables are related to the practice in hospitals. This implies that the managerial aspect of providing health services to patients in hospitals is becoming increasingly important. Hospitals, on the one hand, want to reduce costs and improve their financial assets, while on the other hand they want to maximize the level of patient satisfaction. One unit that is of particular interest within this respect is the operating theater. Since this facility is the hospital's largest cost and revenue center [133, 178], it has a major impact on the performance of the hospital as a whole. Managing the operating theater, however, is hard as it unites many stakeholders like surgeons, managers, trustees or nurses, who may have conflicting preferences and priorities [113]. The operating theater furthermore has to cope with the scarcity of costly resources to anticipate the increasing demand for surgical services caused, amongst other, by the aging population [89]. Next to the costs of the operating rooms themselves and the inherent complexity of the surgeries, the linking aspect of the operating theater to other facilities, for instance the hospital wards or the instrument sterilization facility, contributes to its importance. The central role of the surgical planning and scheduling process in a medical setting hence makes it an interesting and promising subject for improvement identification. It furthermore clearly stresses the need for efficiency and necessitates the development of adequate planning and scheduling procedures. The field of operations research and operations management may assist in the development of such procedures [39, 207]. In this dissertation we develop planning and scheduling procedures that contribute to a better management of the operating theater, and hence may result in an improved hospital practice as a whole.

This dissertation mainly deals with planning and scheduling procedures that apply to an outpatient setting. This means that we focus on elective patients, i.e. patients for whom the surgery can be well planned in advance, who are admitted to and discharged from the hospital on the same working day (see Section 2.2). Surgeries that are performed in such an outpatient setting are often referred to as day surgeries, day cases or ambulatory surgeries. Using a questionnaire in 2004, the International Association for Ambulatory Surgery revealed a rising trend in ambulatory surgery amongst its member countries because of the progress in surgical expertise and the introduction of new anaesthetic and analgesic medications [269]. In Belgium, the share of ambulatory surgeries already equals 30% of the total surgical activity. The International Association for Ambulatory Surgery furthermore considers that at least 75%, if not more, of all procedures will ultimately be carried out in an ambulatory setting [139].

Figure 1.3 clearly illustrates the increasing share of day surgery over time. In particular, it shows for four procedure types, namely cataract, tonsillectomy, inguinal hernia and varicose veins, to what extent they are performed as day surgery in Belgium in 1995, 1997 and 2004. From the figure, it seems that procedures which were previously performed in an inpatient setting, i.e. elective, hospitalized patients who have to stay overnight, now are performed as day surgery. Moreover, there seems to be a quick change: in less than 10 years, the percentage of, for instance, tonsillectomy surgeries increased by about 60 percentage points. Although there seems to be a steady increase in the percentage of surgeries performed as day surgery, the switching degree significantly fluctuates according to the specific procedure types within a single country. There is also no guarantee that procedure types that are frequently performed in an ambulatory setting in one country, are also popular as day surgery in some other country. This statement can be verified by Figure 1.4. Over 90% of tonsillectomy surgeries in Belgium are performed in a day-care setting, whereas ambulatory tonsillectomy surgeries in England only account for less than 10%. Figure 1.4 furthermore shows that countries that outperform others on the day surgery rate for a specific procedure type, may exhibit lower rates for some other procedure types. Belgium, for instance, seems to be the leading country when it comes to tonsillectomy surgeries. With respect to the percentage of varicose veins surgeries that are performed in a day-care setting, however, Belgium is ranked seventh. The

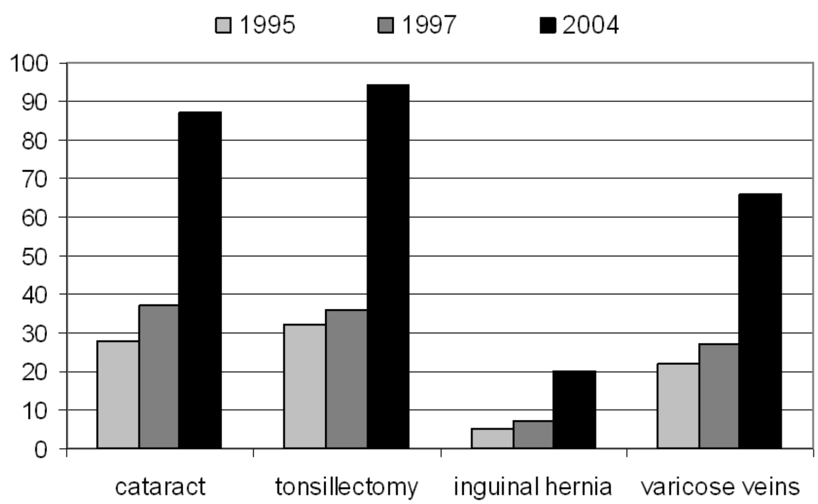

Figure 1.3: Percentage of cataract, tonsillectomy, inguinal hernia and varicose veins surgeries that were performed in Belgium as day surgery in 1995, 1997 and 2004 ([269])

global idea, however, is that the share of day surgeries is large and rapidly increasing. Therefore, it provides a relevant context for scientific research. More detailed information on the share of day surgery over the different countries and procedures can be found in [49, 50, 269].

Again, the explanatory variables that were addressed in one of the previous paragraphs can be consulted to understand the differences in day surgery rates. Moreover, outpatient surgery exhibits some particular advantages over inpatient surgery [141]. First, there are many advantages for the patients themselves. They spend less time in the hospital, recover in their own home and they are less exposed to last minute cancelations due to, for instance, emergency admissions. Day surgery also tends to be less stressful, especially for children, and reduces the risk of cross-infection as they are separated from sicker patients. In short, day surgery leads to an increased patient satisfaction. Second, day surgery is advantageous for the hospital. As procedures are typically short and standardized, uncertainty is reduced and hospitals can manage their schedule more efficiently. It is attractive to

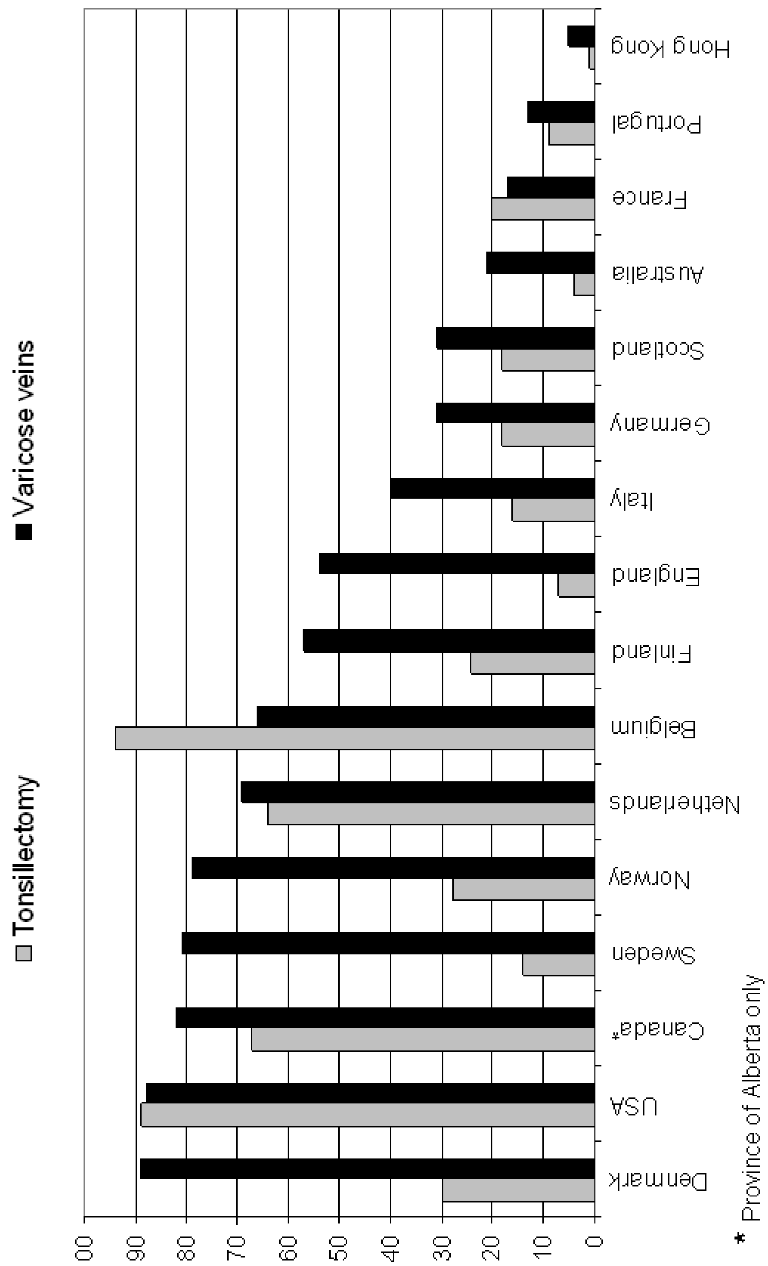

Figure 1.4: Percentage of tonsillectomy and varicose veins surgeries that were performed as day surgery in 2004: a cross-country view ([269])

nurses as night and weekend shifts are not requested. It also enables hospitals to improve patient throughput and to reduce waiting lists (e.g. due to the shortened stay of patients). Third, next to the hospitals, also health care funders benefit from the cost-effectiveness of day surgery.

1.2 Organization of the dissertation

In the previous section we pointed at the importance of health care services in today's society. We illustrated that hospitals play a major role in the delivery of these services and we identified the operating theater as their engine. We furthermore indicated that this dissertation deals with planning and scheduling processes within the operating theater, mainly from an outpatient perspective, and pointed at the increasing importance of ambulatory surgery or day surgery. In this section, we further specify the research content of this dissertation and describe its organization in terms of chapters.

Chapter 2 provides a detailed and structured literature review that covers the recent developments in operating room planning and scheduling. We discuss scientific contributions that appeared in or after 2000 as long as their focus is restricted to operating room planning (i.e. capacity planning) or surgery scheduling (i.e. including a timetabling element). The scope of this literature review is furthermore widened to both elective and non-elective surgery planning and scheduling. This should provide a better perspective to understand the particularities of the outpatient setting, which will be addressed in detail from Chapter 5 on.

One of the findings that appears from the literature review is the lack of a clear and consistent scheme to classify the contributions on operating room planning and scheduling. This results, amongst other, in the ambiguous use of terminology and unclear problem descriptions. Therefore, we propose in Chapter 3 a concise classification scheme, based on the organization of the literature review of Chapter 2, to classify operating room planning and scheduling problems. This way we hope to provide some guidance and clarity in future scientific research.

In Chapter 4 we examine the current state of operating theater planning and scheduling in Flanders (Belgium). Results of 52 respondents who answered the electronic questionnaire, are summarized. These results both relate to the development of the surgery schedule and its realization in practice. One major finding of the survey, which is also confirmed by the literature review of Chapter 2, is that hospitals only have limited access (voluntarily or not) to the algorithms and procedures that may assist in the planning and scheduling process. In our opinion, theory and practice should join forces to obtain real societal contributions. In the next two chapters, we elaborate on this proposition and verify whether we are able both to develop algorithms for a specific combinatorial optimization problem and to efficiently apply them.

Chapter 5 constitutes the main chapter of this dissertation. We introduce a scheduling problem in which we have to sequence surgeries within the operating rooms of a freestanding ambulatory day-care center. The sequencing problem at hand originated from the UZ leuven, which is the academic hospital of the Katholieke Universiteit Leuven. Next to a detailed problem description, the chapter features multiple solution approaches to solve the daily sequencing problem. While most of the approaches are mixed integer linear programming (MILP) based, we also describe a dedicated branch-and-bound approach. We provide computational results of the solution procedures using an artificial test set that was generated using both real and expert data.

Although the algorithmic approaches of Chapter 5 satisfy their goal and hence produce optimized surgery schedules, they are not user-friendly and hard to modify when used in practice. Therefore, we developed a graphical user interface (GUI) that substantially facilitates the use of the algorithms with respect to the input of data, the output of results and the flexibility to change settings. The introduction of such a visual shell clearly enhances the end-user's ability to evaluate various schedules and gain insights that are otherwise hard to capture. In addition to the presentation of this GUI, we report in Chapter 6 on its application at the day-care center of the UZ Leuven Campus Gasthuisberg.

This dissertation concludes with Chapter 7, which summarizes the major issues that were addressed in all preceding chapters. Furthermore, directions for future research on operating room planning and scheduling are provided.

Chapter 2

Literature review

In the past 60 years, a large body of literature on the management of operating theaters has evolved. Magerlein and Martin [180] review the literature on surgical demand scheduling and distinguish between advance scheduling and allocation scheduling. Advance scheduling is the process of fixing a surgery date for a patient, whereas allocation scheduling determines the operating room and the starting time of the procedure on the specific day of surgery. Blake and Carter [24] elaborate on this taxonomy in their literature review and add the domain of external resource scheduling, which they define as the process of identifying and reserving all resources external to the surgical suite necessary to ensure appropriate care for a patient before and after an instance of surgery. They furthermore divide each domain in a strategic, administrative and operational level. Przasnyski [232] structures the literature on operating room scheduling based on general areas of concern, such as cost containment or scheduling of specific resources. Other reviews, in which operating room management is covered as a part of global health care services, can be found in [31, 229, 257, 294].

The aim of this literature review chapter is threefold. First, we want to provide an updated overview on operating room planning and scheduling that captures the recent developments in this rapidly evolving area. In order to maintain a homogeneous set of contributions, we restrict the focus to manuscripts that explicitly incorporate planning and scheduling considerations. *Planning*, on the one hand, is described by the Blackwell Encyclopedic Dictionary of Operations Management [254] as "the process of reconciling supply and demand" (i.e. dealing with capacity decisions). *Scheduling*, on the other hand, is described as "defining the sequence and time allocated to the activities of an operation. It is the construction of a detailed timetable that shows at what time or date jobs should start and when they should end". We do not enlarge the scope of the review to operating room management and hence exclude topics such as business process re-engineering, the impact of introducing new medical technologies, the estimation of surgery durations or facility design. Second, we want to structure the obtained information in such a way that research contributions can easily be linked to each other and compared on multiple facets, which should facilitate the detection of contributions that are within a specific researcher's area of interest. In Section 2.1, we describe how the structure of this review chapter contributes to this goal. Third, pooling literature in a detailed manner enables the identification of issues that are currently (not) well covered and examined.

We searched the databases *Pubmed*, *Web of Science*, *Current Contents Connect* and *Inspec* on relevant manuscripts on operating room planning and scheduling. Furthermore, references that were cited in the manuscripts were reviewed for additional publications, which eventually led to a set of 247 manuscripts. As can be seen from Figure 2.1 (a), this set largely consists of articles published in scientific journals. Proceedings, working papers, Ph.D. dissertations and other manuscripts, such as books or chapters of books, capture the remainder of the research contributions. Figure 2.1 (b) furthermore shows that almost half of the contributions appeared in or after 2000, which clearly illustrates the increasing interest of researchers in this domain. Since the total number of manuscripts is large and our main interest is directed towards the recent advances proposed by the scientific community, we restrict the set of manuscripts that will be addressed in this literature review to those published in or after 2000. We furthermore limit the contributions to those that are written in English in order to augment the review's accessability. A reference to each manuscript of the original set, though, is included in this dissertation's bibliography as they may be valuable to the reader.

2.1 Organization of the review

Researchers frequently differentiate between strategic (long term), tactical (medium term) and operational (short term) approaches to situate their planning or scheduling problem. With respect to the operational level, a further distinction can be made between offline (i.e. before schedule execution) and online (i.e. during schedule execution) approaches. The boundaries between these major categories, however, may vary considerably for different settings and are hence often perceived as vague and interrelated [254]. Furthermore, this categorization seems to lack an adequate level of detail. Other taxonomies may, for instance, be structured and categorized on a specific characteristic of the papers, such as the use of solution or evaluation techniques. However, when a researcher is interested in finding papers on operating room utilization, a taxonomy based on solution technique does not seem very helpful. Equivalently, a taxonomy based on performance measures is not accurate when the reader wants to identify papers that deal with stochastic optimization. Therefore, we propose a literature review that is structured using descriptive fields. Each field analyzes the manuscripts from a different perspective, which may be either problem or technically oriented. In particular, we distinguish between 7 fields:

- *Patient characteristics (Section 2.2)*: reviewing the literature according to the elective (inpatient or outpatient) or non-elective (urgency or emergency) status of the patient.

- *Performance measures (Section 2.3)*: discussion of the performance criteria such as waiting time, patient deferral, utilization, makespan, financial value, preferences or throughput.

- *Decision delineation (Section 2.4)*: indicating what type of decision has to be made (date, time, room or capacity) and whether this decision applies to a medical discipline, a surgeon or a patient (type).

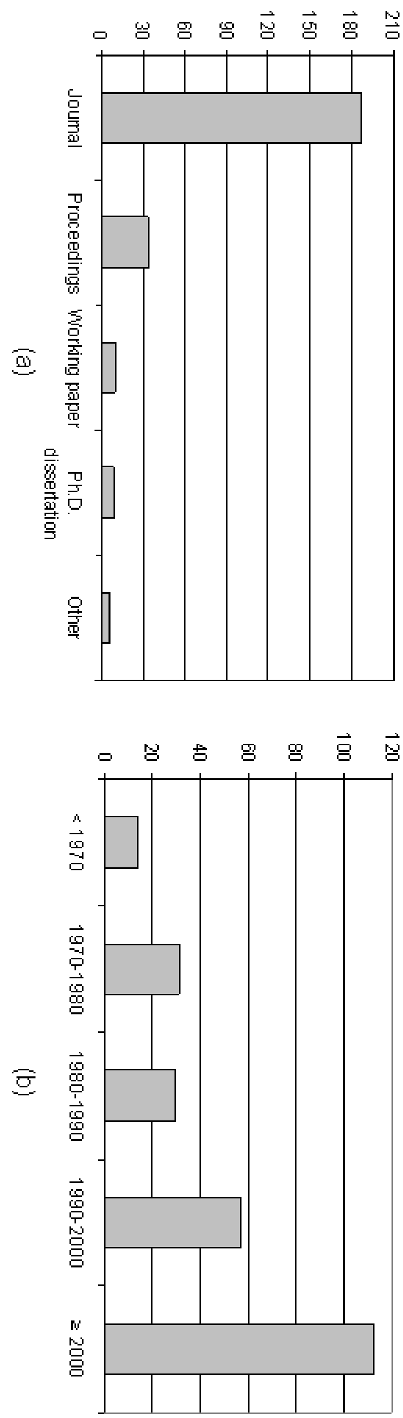

Figure 2.1: Number of research contributions on operating room planning and scheduling (up to 2008) classified according to the manuscript type (a) and the year of appearance (b)

- *Type of analysis (Section 2.5)*: distinguishing between an optimization problem, a decision problem, a scenario analysis, benchmarking (data envelopment analysis) or a complexity analysis.
- *Solution technique (Section 2.6)*: overview of the solution procedures retrieved from the manuscript set, such as mathematical programming methods, constructive and improvement heuristics, simulation or analytical approaches.
- *Uncertainty (Section 2.7)*: indicating to what extent researchers incorporate arrival or duration uncertainty (stochastic versus deterministic approaches).
- *Applicability of research (Section 2.8)*: information on the testing (data) of research and its implementation in practice.

Each section consists of a brief discussion of the specific field based on a selection of appropriate manuscripts and clarifies the terminology when needed. Furthermore, a detailed table is included in which all relevant manuscripts are listed and categorized. Pooling these tables over the several fields should enable the reader to reconstruct the content of specific papers. They furthermore act as a reference tool to obtain the subset of papers that correspond to a certain characteristic. Figure 2.2 illustrates the spreadsheet that underlies the tables of this chapter and that was constructed while reviewing the manuscripts.

Note that the introduction of the 7 descriptive fields may be seen as a first attempt to classify and categorize the literature on operating room planning and scheduling. In Chapter 3 we elaborate on this remark and propose a classification scheme that embeds the logic of this literature review.

2.2 Patient characteristics

Two major patient classes are considered in the literature on operating room planning and scheduling, namely elective and non-elective patients. The former class represents patients for whom the surgery can be planned in

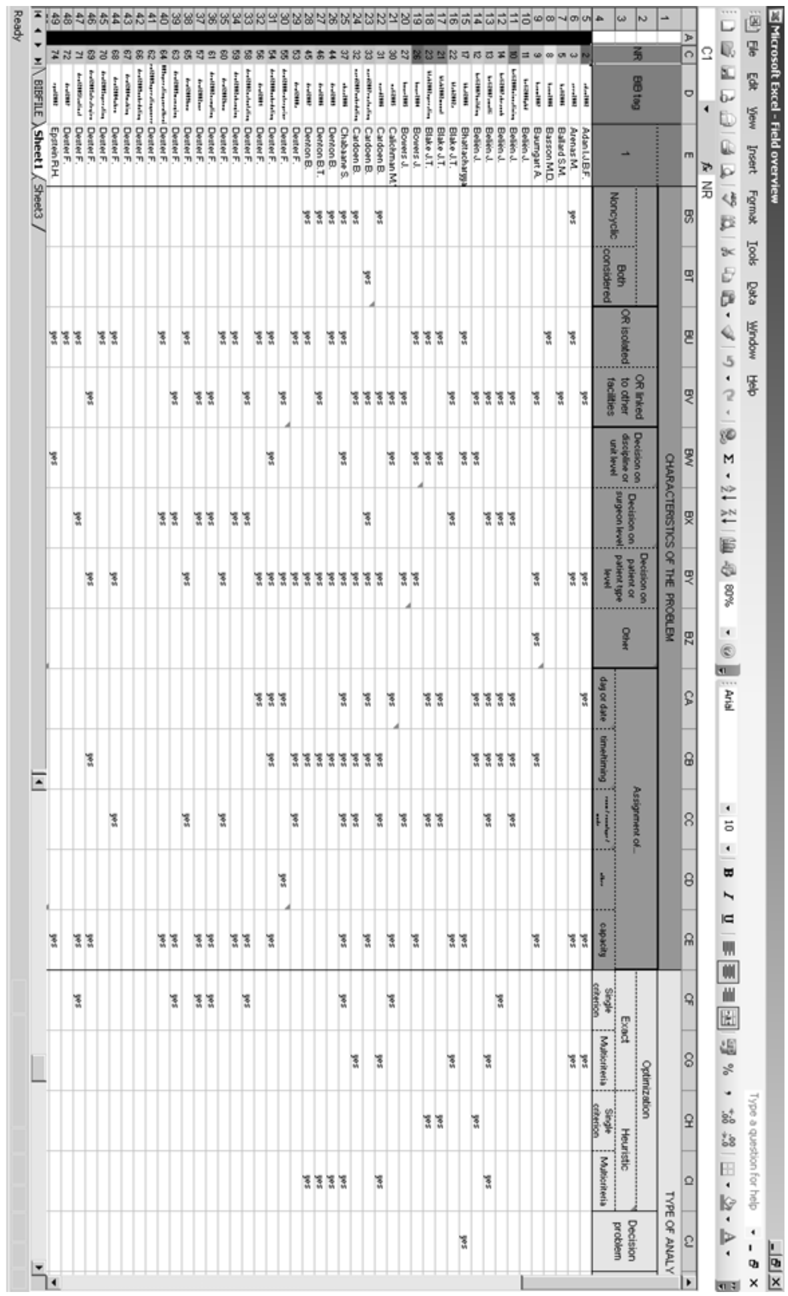

Figure 2.2: Snapshot of the spreadsheet that was constructed while reviewing the manuscripts. Each manuscript is represented by a row. Within each field, specific characteristics of the manuscript are highlighted and documented when needed

advance, whereas the latter class groups patients for whom a surgery is unexpected and hence needs to be performed urgently. It should be clear that papers possibly have multiple entries in Table 2.1. This enables the reader to identify papers that combine multiple patient classes in their research setting. For ease of reference, we printed the papers that combine both elective and non-elective patients in italics.

As shown in Table 2.1, the literature on elective patient planning and scheduling is rather vast compared to the non-elective counterpart. Although many researchers do not indicate what type of elective patients they are considering, some distinguish between inpatients and outpatients. Inpatients refer to hospitalized patients who have to stay overnight, whereas outpatients typically enter and leave the hospital on the same day. Adan and Vissers [2] consider both inpatients and outpatients in their research. They formulate a mixed integer programming model to identify the cyclic number and mix of patients that have to be admitted to the hospital in order to obtain the target utilization of several resources such as the operating theater or the intensive care unit (ICU). In their case, outpatients are treated as inpatients with a length of stay of one day who do not necessarily need specialized resources such as the ICU.

When considering non-elective patients, a distinction can be made between urgent and emergent surgery based on the responsiveness to the patient's arrival (i.e. the waiting time until the start of the surgery). The surgery of emergent patients (emergencies) has to be performed as soon as possible, whereas urgent patients (urgencies) refer to non-elective patients that are sufficiently stable so that their surgery can possibly be postponed for a short period. Table 2.1 indicates that the impact of planning and scheduling non-elective patients is hardly ever studied in an isolated way, i.e. without the incorporation of elective patients. Wullink et al. [293] examine whether it is preferred to reserve a dedicated operating room or to reserve some capacity in all elective operating rooms in order to improve the responsiveness to emergencies. Using discrete-event simulation they found that the responsiveness, the amount of overtime and the overall operating room utilization

Table 2.1: Patient characteristics

elective	
inpatient	[2, 7, 15, 14, 18, 34, *38*, 69, 70, 71, 104, *159*, *197*, *201*, 206, *226*, 265, 272, 276, *278*, *295*]
outpatient	[2, 7, 16, 34, *38*, 55, 60, 61, 67, 69, 70, 71, 97, 136, *159*, *197*, *201*, 206, *226*, 265, 272, *278*, *295*]
not specified	[4, *33*, 37, 53, 54, 59, 65, 66, 73, 78, 80, 85, *90*, 94, 95, 96, 127, 128, *131*, 152, 154, *157*, *165*, *166*, *167*, 169, *181*, 185, 189, 205, 216, 218, 220, 221, 222, 223, *224*, 239, 240, 244, 247, 267, *274*, *275*, 277, 283, 284, 285, *293*]
non-elective	
urgent	[22, *33*, *90*, *181*, *201*, *226*]
emergent	[*38*, *131*, *165*, *166*, *167*, *197*, *224*, *226*, *274*, *278*, *293*, *295*]
not specified	[*157*, *159*, *275*]

significantly improved when the reserved capacity was spread over multiple operating rooms. Bowers and Mould [33] group orthopaedic urgencies into trauma sessions and use Monte-Carlo simulation to determine which session length balances the amount of session overruns with an acceptable utilization rate. They furthermore provide both a discrete-event simulation model and an analytical approximation to explore the effects of including elective patients in the trauma session. Marcon and Dexter [181] study the impact of seven rules for sequencing patients on the hourly number of patients staying in the post-anesthesia care unit (PACU). They also report on the economic impact of the rules on overutilized operating room time, on PACU completion time, and on the percentage of the days with at least one PACU delay that results from reducing the PACU nurse staffing. Non-elective (urgent) cases are included and studied explicitly in the sensitivity analysis where the impact from adding urgent cases to the end of the OR workday on the end-points of the sequencing rules is measured. The best results were obtained with sequencing rules that smooth the flow of patients entering in the PACU, while the frequently applied LCF (*longest case first*) rule and similar rules generate more overutilized operating room time, require more PACU nurses during the workday, and result in more days with at least one delay in PACU admission. Pham and Klinkert [226] model their optimization problem as a multi-mode blocking job shop problem and develop a mixed integer linear programming (MILP) formulation to minimize performance criteria such as the resulting makespan or the incurred operating room overtime. Each job or surgery is described as a predetermined sequence of activities and a maximum allowed waiting time between the processing of two consecutive activities is specified (precedence and time lag). Precedence relations or priorities may further be imposed to surgeries in order to resolve conflicts on shared resources. Furthermore, they allow to incorporate urgency deadlines for certain activities (due date) or lower bounds on the execution time (release date). Emergency cases should be scheduled for a prompt start within two hours after their arrival, which can delay or even bump some elective cases. The authors model the problem of scheduling these emergencies as the job insertion problem in the multi-mode blocking job problem. To keep the system stable, only a *today part* of the established schedule can be rescheduled.

One can question why the majority of the papers focuses on elective patients and ignores the problems caused by non-elective patients. This observation is even more striking when one realizes that the larger degree of uncertainty is the main reason why operating room scheduling requires other scheduling methodologies than the machine scheduling procedures developed for industrial systems. Many authors describe the degree of uncertainty as a motivation for their work and use it to justify the need for developing a dedicated scheduling procedure. Since non-elective patients are, by definition, much more stochastic than their elective counterparts, one would expect that most research efforts focus on this type of patients. A possible explanation is that, since non-elective patients arrive randomly, it is much harder to efficiently schedule them. One can only try to provide enough capacity to deal with them (i.e. restricting the focus to the planning facet). As has been argued by Beliën and Demeulemeester [14], the capacity available to treat non-elective patients is often directly linked to the schedule of the elective patients. Nevertheless, we believe that the problem of non-elective patients is currently too much overlooked in the literature. A second observation is the large amount of papers that do not (explicitly) specify the type of patients for which the scheduling procedures are developed. Generally, the lack of a clear definition of the scope of an operating room planning or scheduling technique is an important shortcoming in many studies.

2.3 Performance measures

The general purpose of all papers that are included in this review can be summarized as "to better streamline the operating room planning and scheduling process and as such to deliver care more efficiently". However, this objective has been translated into many diverse performance criteria that are used to evaluate the resulting procedures. We distinguish between eight main performance measures, namely waiting time, throughput, utilization, leveling, makespan, patient deferrals, financial measures and preferences. We discuss the performance measures in the next paragraphs and clarify their meaning and importance by means of some interesting research contributions. An overview of the manuscripts, classified according to the performance measures, is provided by Table 2.2.

Long waiting lists are among the most heard complaints in general health care, which justifies the many studies aiming at decreasing the waiting times for patients. Also the decrease in surgeon waiting time has been the subject of many research efforts, as the surgeon is a very expensive resource in the operating room. Denton et al. [54] examine how case sequencing affects patient waiting time, operating room idling time (i.e. surgeon waiting time) and operating room overtime. They formulate a two-stage stochastic mixed integer program and propose a set of effective solution heuristics that are easy to implement. Note that patient waiting time may also be interpreted as the stay on a surgery waiting list.

The second objective, throughput, is closely related to patient waiting time. The dependency between waiting time, on the one hand, and throughput, on the other hand, is clearly stated in the well known *Law of Little*, i.e. the average inventory in a system equals the average cycle time (which includes the waiting time and the process time) multiplied by the average

Table 2.2: Performance criteria

waiting time	
patient	[4, 22, 38, 43, 53, 54, 55, 76, 90, 97, 120, 121, 143, 144, 154, 157, 169, 173, 201, 205, 222, 223, 224, 247, 274, 278, 293, 295]
surgeon	[53, 54, 121, 169, 185]
throughput	[7, 11, 38, 97, 131, 244, 247, 267, 278]
utilization	
underutilization / undertime	
operating room	[2, 58, 61, 62, 70, 80, 81, 82, 85, 94, 95, 96, 127, 143, 144, 152, 167, 169, 189, 205, 216, 221, 265, 272, 285, 295]
ward	[2, 285]
ICU	[2, 285]
overutilization / overtime	
operating room	[2, 33, 38, 43, 53, 54, 57, 58, 61, 62, 70, 80, 81, 82, 85, 94, 95, 96, 120, 121, 128, 143, 144, 152, 165, 166, 167, 169, 181, 184, 189, 205, 216, 221, 222, 226, 240, 247, 265, 267, 272, 274, 275, 285, 293]
ward	[2, 38, 285]
ICU	[2, 216, 285]
PACU	[55]
general	
operating room	[7, 11, 22, 33, 34, 38, 61, 71, 78, 90, 97, 128, 131, 169, 205, 206, 224, 247, 267, 272, 274, 275, 276, 293]
ward	[34, 38, 90, 131]
leveling	
operating room	[16, 76, 184, 185, 205]
ward	[15, 14, 18, 127, 244, 265, 277]
PACU	[16, 136, 181, 182]
holding area	[182]
patient volume	[205, 265]
makespan	[95, 96, 136, 181, 220, 226]
patient deferral / refusal	[4, 33, 38, 90, 104, 131, 154, 222, 223, 224, 247, 267]
financial	[25, 37, 59, 60, 61, 65, 66, 67, 69, 71, 73, 121, 159, 173, 197, 206]
preferences	[18, 25, 157, 216, 265, 267, 283, 284]
other	[10, 22, 27, 28, 43, 63, 82, 97, 119, 127, 165, 166, 167, 173, 181, 206, 218, 222, 226, 239, 240, 267, 272, 276, 277, 284]

throughput. The papers classified under throughput focus on increasing the number of treated patients, which obviously leads indirectly to shorter waiting times. In their study, VanBerkel and Blake [278] use discrete-event simulation to examine how a change in throughput triggers a decrease in waiting time. In particular, they affect throughput by changing the capacity of beds in the wards and by changing the amount of available operating room time. Note that the location of their operating rooms is spread over multiple sites, which is a problem setting that is rarely addressed in the literature (see Section 2.4). One can question why the third factor in the Law of Little, inventory, has never been the subject of operating room planning and scheduling research. A possible explanation lies in the fact that patients are living humans, making them unsuitable for the classic inventory models developed for industrial applications. It would, however, be interesting to know whether these models could be adapted to make them useful for operating room planning applications.

A third widely studied objective is utilization. Especially the utilization rate of the operating room has been the subject of recent research. On the one hand, utilization should be maximized as underutilized operating rooms represent unnecessary costs. On the other hand, an operating room that is fully planned with cases and without any time buffers, is very unstable and exhibits large uncertainty costs. The slightest change (e.g. a surgical procedure that takes longer than planned) may cause high costs like staff overtime costs and patient deferrals. Many studies elaborate on this trade-off and evaluate procedures based on the OR efficiency, which is a measure that incorporates both the underutilization and the overutilization of the operating room [58, 61, 62, 70, 80, 81, 82]. As shown in Table 2.2, we relate underutilization to undertime and overutilization to overtime, although they do not necessarily represent the same concept. Utilization actually refers to the workload of a resource, whereas undertime or overtime includes some timing aspect. It is hence possible to have an underutilized operating room complex, although overtime may occur in some operating rooms. Consider, for instance, two operating rooms with a daily capacity of 4 hours. When we assume that operating room 1 (room 2) has a surgical workload of 2

(5) hours, only 7 out of 8 operating room hours are used. Although this operating theater is underutilized, one hour of overtime in operating room 2 is incurred. We prefer, though, to group underutilization and undertime, on the one hand, and overutilization and overtime, on the other hand, as it is unclear in many manuscripts which view is applied. Remark that underutilization and overutilization implicitly refer to a target utilization level of 100%. Van Houdenhoven et al. [275], though, state that setting this target level is a strategic decision and that deviations from this target should be minimized. Since the operating room schedule affects other facilities in the hospital, researchers also focused on the utilization of resources other than the operating room, such as wards or the ICU, though to a lesser extent. The reason probably can be found in the growing trend towards outpatient care (see Chapter 1). In Section 2.2 we already introduced the example by Adan and Vissers [2] in which the deviation between the target utilization of resources such as the ICU staff, ICU beds or regular ward beds is minimized. Vissers et al. [285] furthermore provide a case study in which they illustrate this approach for a department of cardiothoracic surgery. Note that not even a single paper focuses on the underutilization of the PACU.

A fourth main objective concerns the leveling of resources, i.e. developing operating room schedules that lead to smooth resource occupancies without peaks. Besides the operating room itself, the occupancy of different resources could be considered, such as leveling the bed occupancy, and hence workload, in the wards, in the PACU or in the holding area. The idea here is to minimize the risk of capacity problems caused by unexpected events like longer procedure times or length of stay of patients. Marcon and Dexter [182] use discrete-event simulation to examine how standard sequencing rules, such as *longest case first* or *shortest case first*, may assist in reducing the peak number of patients in both the holding area and the PACU. A similar analysis of such sequencing rules is provided in [181]. In this paper, however, the authors restrict the focus to the PACU and study, amongst other, its makespan and the peak number of patients (see Section 2.2). In both studies, operating rooms are sequenced independently, which resulted in a reduced complexity. It should be clear, though, that this can be done simultaneously as well (see Chapter 5).

The paper by Marcon and Dexter [181], which is discussed in the previous paragraph, already introduced a fifth type of objective that returns in several studies, namely decreasing the makespan (C_{max}). The makespan represents in their case the completion time of the last patient's recovery. In general, it can be defined as the time between the entrance of the first patient and the completion time of the last patient. Although the makespan is often measured for the operating room, their study illustrates that it can also be studied for one of the closely connected resources like the PACU. As decreasing the makespan often involves a dense schedule, we believe this criterion should be combined with protective measures to increase its stability and robustness.

The sixth objective, patient deferral or patient refusal, is indirectly related to throughput and, as explained above, to overutilization and leveling. The papers that explicitly try to minimize the number of deferrals or refusals are classified under this objective. Kim and Horowitz [154] study how to include quotas in the surgery scheduling process in order to streamline the admittance to the ICU. In particular, they try to reduce the number of canceled elective surgeries that result from ICU bed shortages without significantly worsening the waiting times of other patients who are seeking admission to the ICU.

It can be argued that financial objectives are the most general of all studied objectives. Indeed, if an operating room scheduling or planning model leads to cost savings, the saved money can be invested to solve any of the above mentioned problems. For instance, long waiting times can be decreased by installing more capacity. It is our belief that the financial issues are too often overlooked, certainly in well-developed health care nations in which waste of capacity is still a major problem. Given the aging of the population in many of these countries, the financial well being of the health care system should be a main research focus. Some papers examine how adequate planning and scheduling contributes to an increased contribution margin, which is defined as revenue minus variable costs [59, 61, 65, 66, 67, 71]. It should be noted that research efforts are not limited to the identification of the best practice. Dexter et al. [60] formulate a linear programming model in which the variable costs are maximized in order to determine the worst case scenario.

A last category of objectives incorporate the preferences of the different parties involved in the operating room process. Surgeons can have different preferences regarding the timing of assigned operating room block time, patients can have different preferences with respect to the timing of their surgery. At first sight, this set of objectives seems to be less important. However, various studies report on the relationship between the efficiency of care and the schedules that take into account these preferences, as illustrated in Table 2.2. In Chapter 5 we develop algorithms that incorporate preferences such as the timely scheduling of children and prioritized patients. At the same time, patients with a substantial travel distance to the ambulatory surgery center preferably have to be scheduled after a certain time period.

Table 2.2 also depicts manuscripts that describe other performance measures than those that were addressed in the previous paragraphs. This category groups criteria related to, for instance, delays in PACU admissions [63, 181], operating room target allocation [27, 28, 43, 239] or the use of additional capacity of specific resources, such as the number of operating room openings [119, 240, 276, 277] or the demand for extra capacity of beds in wards [222].

2.4 Decision delineation

A variety of planning and scheduling decisions with a resulting impact on the performance of the operating theater are studied in the literature. In Table 2.3, we provide a matrix that indicates what type of decisions are examined in the manuscripts. We distinguish between decisions that are related to the assignment of a date, a time indication, an operating room or capacity. The decisions that are related to a date can be very specific (e.g. Thursday 11 December 2008) or vague (e.g. in January, on Monday or in week 35). The time indication points at the timing of an activity on a particular day. Similarly to the assignment of a date, the time indication can be specific (e.g. at 11 a.m.) or rather vague (e.g. in the morning session). The choice of an operating room constitutes a next type of decision (e.g. operating room 2 or operating room of type A). The final type of decision concerns the allocation of capacity (e.g. the total amount of operating room time available on a particular day). The manuscripts are furthermore categorized according to the decision level they address, i.e. to whom the particular decisions apply. We distinguish between the discipline, the surgeon and the patient level. We deliberately choose to avoid the classification into the three classical levels: case mix planning, master surgery scheduling and patient scheduling adopted by many authors to define the scope of their planning or scheduling problem. The reason is twofold. First, there are no clear definitions of these three decision levels. Various authors classify different problems into the same class. To give an example: Blake et al. [27], Blake and Donald [28], Beliën and Demeulemeester [14] and Beliën et al. [16] define a master surgery schedule as a schedule that specifies the number and type of operating rooms, the hours that operating rooms are available, and the specialty that has priority at an operating room. This definition has also been incorporated by Testi et al. [267]. Van Oostrum et al. [277], however, define a master surgery schedule as a schedule that specifies for each *OR-day combination* of the planning cycle a list of recurring surgical procedure types that must be performed. Although all the above papers [14, 16, 27, 28, 267, 277] claim to construct a cyclic master surgery schedule, it should be clear that the granularity of the outcome differs according to the decision level or perspective chosen by the authors. A similar reasoning applies to case mix planning since the available amount of operating room time (capacity) may be divided according to disciplines, surgeons or patient types. It would be worthwhile to determine adequate definitions for various concepts such as master surgery scheduling, tactical scheduling or case mix planning for future use. This, however, cannot be done by a single researcher as opinions about the concepts vary widely amongst the scientific community. Therefore, many experts should take part in the exercise so that the opinions may converge, for instance by applying the Delphi methodology, to acceptable and clear definitions. Second, we believe that our two-dimensional classification of planning and scheduling decisions (see Table 2.3) provides much more detail on the exact type of decisions that take place. We clarify this point in the next paragraphs.

The discipline level unites contributions in which decisions are taken for a medical specialty or department as a whole. Blake et al. [27] and Blake and Donald [28] report on an integer programming model and an improvement heuristic to construct a cyclic timetable that minimizes the underallocation of a specialties' operating room time with respect to its predetermined target time. The model determines for each specialty what operating room types are assigned to what days of the week, i.e. a decision concerning date and room.

At the surgeon level, Beliën et al. [16] introduce a software tool in which decisions for specific surgeons, instead of disciplines, are considered. For each surgeon, the planner has to decide on what day and in which room surgeries have to be performed. Since operating rooms may be divided in a morning and an afternoon session, the block assignments also incorporate a time indication. The impact of the cyclic timetable decisions on the use of various resources, such as nurses, artroscopic towers or lasers, is visualized and guides the planner in improving the constructed surgery schedule. Since the amount of operating room time for each surgeon in the planning horizon is predetermined, no capacity decisions have to be made.

Next to the discipline and surgeon level, Table 2.3 also specifies a patient level. On this level, decisions are made for individual patients or patient types. Although patient types may represent the distinction between, for instance, elective or non-elective patients, they frequently refer to surgical procedure types. This view is incorporated by van Oostrum et al. [277]. Starting from a list of recurring procedure types, i.e. types that are frequently performed and hence have to be scheduled in each planning cycle, they decide what mix of procedures will be performed on what day and in which operating room. They aim at the minimization of the number of operating rooms in use, on the one hand, and the leveling of the hospital

Table 2.3: Type and level of decisions

	discipline level	surgeon level	patient level	other
date	[14, 27, 28, 37, 43, 239, 244, 247, 267, 295]	[15, 16, 18, 38, 152, 223]	[2, 38, 43, 71, 73, 76, 90, 94, 95, 96, 120, 121, 127, 128, 143, 144, 152, 154, 157, 165, 166, 167, 205, 216, 221, 222, 223, 226, 240, 244, 247, 265, 267, 276, 277, 284, 285]	
time	[14, 131]	[15, 16, 18, 38]	[11, 38, 43, 53, 54, 55, 57, 63, 73, 95, 96, 121, 131, 136, 143, 144, 157, 169, 181, 182, 185, 220, 226, 240, 247, 267, 274, 283]	
room	[27, 28, 43, 239, 244, 247, 267, 295]	[16, 18, 152, 223]	[34, 43, 57, 70, 80, 81, 94, 95, 96, 120, 127, 128, 143, 144, 152, 157, 165, 167, 181, 184, 185, 205, 216, 222, 223, 226, 240, 244, 247, 267, 276, 277, 283, 293]	
capacity	[22, 33, 37, 43, 73, 85, 121, 131, 206, 244, 247, 267, 278, 295]	[25, 38, 59, 60, 65, 66, 67, 69, 78, 152, 159, 223]	[2, 4, 33, 38, 43, 63, 104, 127, 131, 152, 197, 222, 224, 244, 276, 277, 285, 293]	[11, 90, 97, 119, 173, 201, 218, 278]
other	[244, 275]	[76, 205, 223]	[76, 90, 205, 223, 244, 272]	

bed requirements, on the other hand. A two-phase decomposition approach is formulated that is heuristically solved by column generation and mixed integer programming.

Although most manuscripts take only one decision level into account, this does not necessarily have to be the case. Testi et al. [267] report on a hierarchical three-phase approach to determine operating theater schedules. In the first phase, which they refer to as session planning, they determine the number of sessions to be scheduled weekly for each discipline. Since they distribute the available operating room time over the set of disciplines, this problem can be regarded as a case mix planning problem. Phase 2 formulates a master surgery scheduling problem in which they assign an operating room and a day in the planning cycle to the sessions of each discipline. Both phases are solved by integer programming and are situated on the discipline level. Phase 3, on the contrary, is formulated in terms of individual patients. A discrete-event simulation model is presented to evaluate decisions concerning date, room and time assignments. When patients are scheduled consecutively in an operating room, i.e. without incorporation of idle time, the planned surgery starting times (time decision) are determined by sequencing the patients.

We added both a row and a column (*other*) to Table 2.3 to provide entries for manuscripts that study the operating room planning and scheduling problems in a way that is not well captured by the main matrix. Manuscripts that are categorized in this column or row examine, for instance, decisions concerning surgeon-patient combinations [76, 205, 223] or decide in which hospital or site capacity has to be preserved [90, 278].

Most scheduling procedures described in the literature apply to the patient level, while the contributions that apply to the surgeon and discipline level are mainly overlooked, except when the decision concerns the assignment of capacity. A possible explanation is that, unlike patients, surgeons do not easily accept changes in their rosters, and certainly not if these changes are suggested by a computer program. Driven by the continuously growing pressure on resources, today's surgeons more and more realize the need for efficient care and are less averse from operations research scheduling techniques that help to streamline the whole operating room process. We believe that research efforts focusing on the scheduling of surgeons might have a larger success rate in the (near) future and hence result in an increased amount of contributions that are situated on the surgeon level.

In the introduction of this dissertation (see Chapter 1) we already mentioned that operating room planning and scheduling decisions affect facilities throughout the entire hospital. Therefore it seems to be useful to incorporate facilities, such as the ICU or PACU, in the decision process and to try to improve the global performance. If not, improving the operating room schedule may worsen the practice and efficiency of those related facilities. In Table 2.4, we classify the manuscripts according to whether they study the operating theater in isolation or integrate it with other facilities. Within the integrated class we distinguish between papers that study the impact on the PACU, the ICU and the wards. Beliën et al. [16] integrate their master scheduling system with all kinds of user specific resources of which the consumption is directly related to the timing of the surgeries (e.g. the radiology department). Velasquez and Melo [283, 284] use the concept of general resources, without exactly specifying which ones. Therefore, we classify these papers under the category "other".

In 1997, Blake and Carter indicated in their literature review that techniques for integrating operating room scheduling with other hospital operations were urgently required [24]. Table 2.4 shows that still half of the recent contributions limit their scope to an isolated operating room. Although some progress seems to be achieved, a further integration of the operating room with other hospital facilities remains a main topic for future research, especially in combination with the incorporation of uncertainty (see Section 2.7). One of the major reasons for simplifying the research scope probably stems from the increased complexity, both in formulation and in computation, of the decision process caused by the integration. Note that this integration should not be limited to facilities that are situated within one

Table 2.4: Integration of the operating room planning and scheduling process

isolated operating room	[4, 10, 22, 27, 28, 33, 43, 53, 54, 57, 62, 66, 69, 70, 71, 76, 73, 78, 80, 81, 82, 85, 94, 95, 96, 119, 120, 121, 127, 128, 157, 159, 165, 166, 167, 169, 184, 185, 189, 205, 218, 221, 223, 224, 239, 240, 247, 272, 274, 275, 276, 293]
integrated operating room	
PACU	[7, 11, 55, 63, 96, 97, 121, 144, 181, 182, 197, 201, 220, 226]
wards	[2, 15, 14, 17, 25, 34, 37, 38, 59, 60, 65, 67, 90, 104, 121, 127, 131, 136, 197, 222, 244, 265, 267, 277, 278, 285, 295]
ICU	[2, 59, 60, 65, 67, 121, 127, 143, 144, 197, 216, 226, 244, 277, 278, 285]
other	[16, 283, 284]

hospital, as studies on multi-facility or multi-site operating room planning and scheduling are currently emerging [90, 244, 278].

2.5 Type of analysis

The way in which operating room planning and scheduling problems are analyzed constitutes the subject of this section. As indicated in Table 2.5, we distinguish between optimization problems, decision problems, benchmark analysis, scenario analysis and complexity analysis. Note that the type of analysis is closely related to the solution technique that is applied to solve the problem and hence to perform the analysis. We opt to separate both subjects, though, as many techniques can be applied to perform one specific type of analysis. We refer to Section 2.6 for a detailed classification of the literature according to the solution or evaluation technique.

A substantial part of the literature on operating room planning and scheduling consists of contributions in which a problem is stated and consecutively optimized. As indicated in Table 2.5, these combinatorial optimization approaches are either exact, i.e. eventually leading to a solution for which optimality can be proven, or heuristic in nature. We furthermore distinguish between single and multiple objective approaches based on the number of performance criteria that need to be optimized. Although it is often stated that heuristic approaches are indispensable to solve practical or real-sized problems efficiently, a number of powerful exact approaches seem to be suggested in the literature, even when multiple criteria are considered. Since the computational effort to solve optimization problems does not only depend on the objective function, but also on the type of constraints that are incorporated in the analysis, we list in Table 2.6 what type of constraints are addressed in the literature. We limit the scope to the occurrence of hard constraints, i.e. constraints or limitations that are never allowed to be violated, as soft constraints are often incorporated as part of the objective function (see Section 2.3).

A first category of hard constraints are those related to the use of resources. As these resources are costly and limited in capacity, they are often binding and hence have a substantial impact on the set of feasible solutions. Note that hospitals may even impose a limit on the allowed amount of operating room overtime or undertime. Second, we identify precedence constraints or constraints related to time lags. Due to contamination risks, for instance, it is obliged to schedule infected patients at the end of the surgery day or to insert idle time between surgeries which allows for an extended cleaning of the operating room (see Chapter 5). A third category consists of constraints related to certain release or due dates, whereas a fourth and last category represents the demand-related constraints. An example of demand-related constraints is provided by Santibanez et al. [244], who study the impact of simultaneously changing the master surgery schedule of multiple hospitals on throughput or the peak use of post-surgical resources. In their MILP formulation, they restrict the amount of operating room blocks (i.e. demand for operating room time) that is assigned to the surgical specialties within each hospital between a lower and upper bound. Equivalently, they state lower and upper throughput bounds for procedure types (i.e. demand for surgery).

Table 2.5: Type of analysis

optimization	
exact	
single criterion	[15, 37, 43, 59, 60, 65, 66, 67, 95, 119, 127, 159, 185, 223, 239, 244, 267, 283]
multicriteria	[2, 4, 18, 25, 94, 143, 144, 152, 166, 197, 216, 221, 222, 226, 265, 284, 295]
heuristic	
single criterion	[14, 27, 28, 184, 189, 220, 274]
multicriteria	[18, 43, 53, 54, 55, 95, 96, 120, 127, 128, 136, 157, 165, 167, 205, 240, 276, 277, 285]
decision problem	[22, 284]
benchmark analysis	[10, 206]
scenario analysis	[2, 7, 11, 16, 22, 25, 33, 34, 38, 53, 54, 55, 57, 59, 60, 65, 67, 69, 70, 71, 73, 78, 80, 81, 82, 85, 90, 95, 97, 104, 128, 131, 136, 144, 154, 159, 169, 173, 181, 182, 184, 189, 197, 201, 205, 206, 216, 218, 222, 224, 244, 247, 267, 272, 274, 275, 276, 278, 285, 293, 295]
complexity analysis	
problem	[54, 95, 96, 120, 127, 128, 136, 143, 144, 152, 157, 165, 166, 167, 184, 220, 240, 274, 277]
solution procedure	[15, 120, 128, 136]

As indicated in Table 2.5, not every analysis related to the planning and scheduling of the operating room is formulated as a traditional optimization problem. Velasquez and Melo [284] exploit the structure of their scheduling problem in which they assign one specific surgery to a specific day in the planning horizon so that penalties related to the use of additional resources or time window violations are avoided, and divide the set of solutions into equivalence classes. Such equivalence classes group solutions with the same objective value. Optimizing the problem hence boils down to solving a decision problem: “Is it possible to obtain a feasible solution in the best

Table 2.6: Type of hard constraints retrieved from operating room optimization approaches

resource constraints	
holding area	[55, 197, 226]
ward	[2, 25, 37, 59, 60, 65, 67, 127, 197, 222, 226, 244, 265, 277, 285]
ICU	[2, 59, 60, 65, 67, 127, 143, 144, 197, 216, 226, 244, 277, 285]
PACU	[55, 96, 144, 197, 220, 226]
equipment	[43, 120, 143, 144, 167, 222, 226, 244, 265]
surgical staff	[2, 15, 25, 55, 95, 119, 120, 128, 143, 144, 152, 157, 205, 216, 221, 223, 226, 240, 244, 265, 267, 276]
budget	[25, 60]
regular operating room time	[2, 4, 15, 14, 18, 25, 27, 28, 43, 59, 60, 65, 66, 67, 95, 96, 127, 143, 144, 152, 159, 165, 166, 167, 185, 189, 205, 216, 221, 222, 223, 226, 239, 240, 244, 267, 276, 285, 295]
operating room overtime / undertime	[43, 95, 96, 120, 127, 143, 144, 167, 216, 226, 240, 267, 277]
other	[53, 220, 240, 283, 284]
precedence constraints / time lags	[143, 185, 205, 223, 226, 274]
release / due date constraints	[43, 94, 95, 96, 120, 143, 144, 157, 165, 166, 167, 221, 226, 240]
demand constraints	[2, 4, 15, 14, 18, 25, 27, 28, 37, 43, 59, 60, 65, 66, 67, 119, 127, 152, 159, 197, 221, 223, 239, 244, 267, 277, 285, 295]

equivalence class, yes or no?”. When no solution exists, a next (inferior) class is examined until a feasible solution is obtained.

Although benchmark studies may also integrate some optimization approach such as data envelopment analysis (DEA), we introduce a separate entry for this type of analysis in Table 2.5. In the DEA methodology, linear programming is used to determine the weights of both inputs and outputs that optimize a decision making unit’s efficiency score. Comparison of a unit with the scores of other units may suggest areas that need to be improved. Basson and Butler [10] apply DEA to operating room activity. They analyze how rankings of sites based on their operating room efficiency scores differ when the types of inputs (e.g. staffing pattern) and outputs (e.g. number of cases performed per equipped operating room) that are taken into account vary. The above paper illustrates the possible contribution of DEA to benchmark studies. The current body of literature, however, does not sufficiently address such studies, although their outcome may be of high importance to the practitioners.

Instead of limiting the focus to the optimization of one specific problem setting, researchers may also focus on the impact that results from changes to the operating room setting under study. We refer to this type of analysis as scenario analysis since multiple scenarios, settings or options are compared to each other with respect to the performance criteria. As indicated in Table 2.5, the literature provides a large set of contributions in which a scenario analysis is addressed. Niu et al. [201] describe a simulation model in which scenarios are tested with adapted resource capacities. In particular, they examine how the length of stay of patients varies according to changes in the number of operating rooms, chairs in the holding unit, beds in the PACU or transporters.

Finally, researchers may also analyze the computational complexity of their combinatorial problem or its corresponding solution approach. Lamiri et al. [166] prove using the 3-partition problem that their stochastic optimization problem, in which they assign patients over a planning horizon in order to minimize the sum of patient related costs and operating room overtime costs, is strongly NP-hard. The authors propose a solution methodology that combines Monte-Carlo simulation and mixed integer programming and elaborate on its convergence to the optimum. We refer the interested reader to Garey and Johnson [105] for an introduction to problem complexity and technical details on this type of analysis. A primer on calculating the computational complexity of algorithmic solution procedures is, for instance, provided in [259].

2.6 Solution technique

The literature on operating room planning and scheduling exhibits a wide range of solution methodologies that are retrieved from the domains of operations management and operations research. We refer to Gass and Harris [107] or Winston and Goldberg [292] for a brief introduction to the various solution techniques that are listed in Table 2.7. In the next paragraphs, we distinguish between mathematical programming, simulation, both constructive and improvement heuristics and analytical procedures.

A first category of solution techniques is mathematical programming. Mulholland et al. [197] report on the application of linear programming to determine the mix of patients that optimizes the financial outcome of both physicians and the hospital, taking into account the resulting consumption of multiple resources such as the ICU, PACU, ward or holding unit. In contrast to linear programming models, quadratic programming models feature a nonlinear objective function. Beliën and Demeulemeester [14] minimize the expected total bed shortage, which is not a linear function of the decision variables, by adapting the master surgery schedule. They provide heuristic solution methods based on, for instance, simulated annealing and quadratic or mixed integer programming to solve both the original problem and an approximate problem setting in which the objective function is linearized. When dealing with multiple objectives, goal programming may serve as a flexible optimization technique. For each objective, a target value or goal is specified. The objective is to minimize the penalized deviations from the targets. Ozkarahan [216] formulates a goal programming

Table 2.7: Solution technique

mathematical programming	
linear programming	[10, 53, 59, 60, 67, 119, 159, 197, 206, 221]
quadratic programming	[14, 18, 65]
goal programming	[4, 25, 205, 216, 239, 265]
mixed integer programming	[2, 14, 18, 27, 28, 43, 127, 143, 144, 152, 165, 166, 222, 223, 226, 240, 244, 267, 277, 285, 295]
dynamic programming	[15, 94, 96, 167, 220]
column generation	[95, 96, 127, 165, 167, 277]
branch-and-price	[15, 94, 283]
other	[66, 185, 220, 221]
simulation	
discrete-event	[7, 11, 33, 34, 38, 63, 71, 73, 78, 80, 85, 90, 97, 131, 154, 173, 181, 182, 184, 201, 222, 224, 247, 267, 272, 274, 278, 293, 295]
Monte-Carlo	[33, 55, 67, 128, 165, 166, 169, 205, 218]
constructive heuristic	[14, 18, 43, 53, 54, 70, 73, 80, 81, 120, 128, 157, 165, 167, 189, 220, 274]
improvement heuristic	
meta-heuristic	
simulated annealing	[14, 18, 55, 128, 274]
tabu search	[96, 136]
genetic algorithm	[96, 240]
other	[27, 28, 54, 63, 128, 165, 167, 184, 274]
analytical procedure	[33, 53, 166, 173, 275]

approach in which surgeries, if they are scheduled, are assigned to operating rooms and in which, amongst other, intensive care capabilities or operating room and surgeon preferences are addressed. Mathematical formulations of operating room planning and scheduling problems with a realistic size often result in a huge set of decision variables. Instead of specifying and adding this entire set of variables in advance, column generation generates and adds variables when needed and hence optimizes the problem with only a subset of the variables. Lamiri et al. [167] describe a column generation approach that assigns patients to surgery days and operating rooms in such a way that patient related costs and operating room utilization costs are minimized. They propose a dynamic programming algorithm to solve the pricing problem, i.e. the subproblem in which promising variables are generated. As column generation cannot force the decision variables to be integer, the authors use the fractional output as input for various constructive and improvement heuristics. However, column generation can also be intertwined with an enumerative branch-and-bound framework in order to obtain integer solutions. This methodology is referred to as branch-and-price and is applied by Fei et al. [94]. They assign surgical cases, who may be characterized by a surgery deadline, to specific days and operating rooms so that the total unexploited or overtime operating cost is minimized. Similarly to [15, 96, 167], they solve the appropriate pricing problem through dynamic programming. Other mathematical programming approaches that are retrieved in the literature on operating room planning and scheduling are based on, for instance, lagrangian relaxation [66, 220].

The literature on operating room planning and scheduling also provides, next to mathematical programming methods, a substantial amount of simulation approaches. As shown in Table 2.7, we distinguish between discrete-event and Monte-Carlo simulation. While discrete-event simulation represents a systems as it evolves over discrete or countable points in time (dynamic), Monte-Carlo simulation represents a system at a particular point in time (static) [292]. Lebowitz [169] applies Monte-Carlo simulation to evaluate and quantify the impact of sequencing procedures on waiting time and operating room utilization criteria. A discrete-event simulation model is designed by Sciomachen et al. [247] in order to evaluate the utilization of operating rooms or medical disciplines, patient throughput and the number of overruns or patient deferrals. In particular, they examined the impact of changing, amongst other, the master surgery schedule and the case sequencing rules on the listed performance criteria. Note that their study largely corresponds with the third phase that is examined in [267].

Dedicated heuristic procedures broadly fall into two main categories, namely constructive and improvement heuristics. Constructive heuristics generally build solutions to planning and scheduling problems from scratch, whereas improvement heuristics perform operations on an existing schedule to transform a solution into an improved one. Guinet and Chaabane [120] present a primal-dual constructive heuristic that assigns patients to surgery days and operating rooms. Their algorithm, which is an extension of the Hungarian method, minimizes both operating room overtime costs and patient hospitalization costs, i.e. costs resulting from the waiting time between the hospitalization date and the intervention date. Hans et al. [128] propose various priority-based constructive heuristics to maximize the capacity utilization of the operating theater and to minimize the risk of overtime by introducing an amount of planned slack time. However, they also elaborate on improvement heuristics such as a random exchange method, which only accepts changes or swaps that yield an improved solution, or a simulated annealing approach, which accepts worse solutions with a low probability in order to leave local optima. Next to simulated annealing, the literature provides contributions that apply other kinds of meta-heuristics. Hsu et al. [136] solve a case sequencing problem by tabu search to minimize both the required number of PACU nurses and the completion time of the PACU's last patient. Roland et al. [240], on the other hand, report on the construction of a genetic algorithm that heuristically minimizes the costs related to operating room openings and overtime. In particular, their scheduling problem, which is closely related to the well-known resource-constrained project scheduling problem, questions what date, operating room and starting time indication should be assigned to the set of surgeries. They validate the performance of the genetic algorithm through a comparison with an MILP approach.

Finally, Table 2.7 also reports on a solution technique that is rather rarely applied to the domain of operating room planning and scheduling. Lovejoy and Li [173] analytically examine whether it is preferred to increase capacity by extending the working hours in the current operating rooms or by building new operating rooms. They evaluate both scenarios with respect to the waiting time to get on the schedule, the start-time reliability of procedures and the hospital profits. In Chapter 5 we introduce a dedicated branch-and-bound procedure to solve a multi-objective case sequencing problem. In contrast to MILP approaches, the dedicated branching and bounding procedures are not based on LP relaxations.

Mathematical programming methods tend to be well applied in the literature on operating room planning and scheduling. One reason for their success stems from the rapidly improving solvers that are offered by commercial firms such as ILOG (www.ilog.com) or Lindo Systems (www.lindo.com). Computational boundaries are continuously widened, even for complex problems that formerly had to be solved heuristically. This trend is likely to continue in the future, as current research efforts are even heading towards the development of a generic branch-and-price solver [279], i.e. a powerful mathematical programming approach that currently only appears in a dedicated and tailored way, according to the specific problem at hand. Next to mathematical programming, also simulation approaches seem to be successful for analyzing operating room planning and scheduling problems. Especially when the problem exhibits a lot of stochasticity or when it is highly interrelated, simulation proves to be useful as it features an extensive modeling flexibility and allows for a sufficient degree of detail. Although most authors who apply simulation restrict their analysis to the evaluation of multiple scenario's, recent approaches can be identified that diverge towards simulation-based optimization and combine simulation with other solution techniques (see [166] for an example).

Table 2.8: Uncertainty incorporation

deterministic	[2, 4, 10, 15, 16, 25, 27, 28, 37, 43, 60, 67, 94, 95, 96, 119, 120, 127, 136, 143, 144, 152, 157, 159, 182, 185, 197, 205, 206, 216, 220, 222, 223, 226, 239, 240, 244, 265, 267, 274, 283, 284, 285, 295]
stochastic	
arrival	[14, 18, 22, 33, 34, 38, 66, 71, 73, 78, 90, 121, 131, 154, 165, 166, 167, 173, 189, 201, 218, 222, 224, 247, 267, 274, 278, 293, 295]
duration	[7, 11, 14, 18, 22, 33, 38, 53, 54, 55, 57, 73, 78, 80, 90, 104, 121, 127, 128, 131, 154, 165, 166, 169, 173, 181, 182, 184, 189, 201, 218, 221, 224, 247, 267, 272, 274, 275, 276, 277, 278, 293, 295]
other	[38, 65, 67]

2.7 Uncertainty

One of the major problems associated with the development of accurate operating room schedules or capacity planning strategies is the uncertainty inherent to surgical services. Deterministic planning and scheduling approaches ignore such uncertainty or variability, whereas stochastic approaches explicitly try to incorporate it. In Table 2.8, we list the relevant manuscripts based on their uncertainty incorporation.

Two types of uncertainty that seem to be well addressed in the stochastic literature are arrival uncertainty and duration uncertainty. The former points, for instance, at the unpredictable arrival of emergency patients or at the lateness of surgeons at the beginning of the surgery session, whereas the latter represents deviations between the actual and the planned durations of activities related to the surgical process. Harper [131] presents a detailed hospital capacity simulation model that enables system evaluations by means of a scenario analysis. The participation of multiple hospitals in the development phase resulted in a generic framework that allows to incorporate uncertainty or trends in the arrival profiles of patient groups as well as duration variability (e.g. length of stay or surgery durations). Persson and Persson [224] describe a discrete-event simulation model to study how resource allocation policies at the department of orthopaedics affect the waiting time and utilization of emergency resources, taking into account both patient arrival uncertainty and surgery duration variability.

Next to arrival and duration uncertainty, other types of uncertainty may be addressed. Dexter and Ledolter [65] examine to what extent uncertainty in the estimated contribution margin of surgeons (characterized by e.g. standard deviations) may lead to inferior allocations of operating room capacity when the goal is to maximize a hospital's expected financial return. Only few manuscripts refer to resource uncertainty (see [38] for an example), while this topic currently is a hot topic in, for instance, project management or project scheduling [164]. It should be noted, though, that resource uncertainty often coincides with arrival uncertainty. For example, the arrival of emergencies may result in a claim of both the surgeon who is needed to perform the emergent surgery and a specific operating room. These claims actually result in resource breakdowns as the elective program cannot be continued and hence has to be delayed.

It should be clear that operations management techniques are able to deal with stochasticity, especially simulation techniques and analytical procedures, and that an adequate planning and scheduling approach may lower the negative impact of uncertainty. Mostly, researchers assume a certain level of variability, for instance by analyzing data, and use this information as input for their modeling phase. However, only limited attention is paid to the reduction of variability within the individual processes. In other words, one should first start to reduce uncertainty in the individual processes instead of immediately focusing on a reduction of the variability of the system that specifies the relation between the individual processes. Think, for instance, of the estimation of surgery durations. Instead of the immediate determination of the distribution of a surgery duration, one should examine whether the population of patients for which the durations are taken into

Table 2.9: Applicability of research

no testing	[58, 62, 76, 119, 121]
data for testing	
theoretic	[15, 14, 53, 70, 73, 81, 85, 90, 94, 96, 120, 143, 144, 157, 165, 166, 167, 169, 181, 184, 205, 220, 223, 226]
based on real data	[2, 4, 7, 10, 11, 16, 18, 22, 25, 27, 28, 33, 34, 37, 38, 54, 55, 57, 59, 60, 65, 66, 67, 69, 70, 71, 78, 80, 81, 85, 95, 97, 104, 127, 128, 131, 136, 152, 154, 159, 173, 182, 185, 189, 197, 205, 206, 216, 218, 221, 222, 223, 224, 226, 239, 244, 247, 265, 267, 274 275, 276, 277, 278, 283, 284, 285, 293, 295]

account is truly homogenous. If not, separating the patient population may result in a decreased variability even before the planning and scheduling phase is executed (see Chapter 6). As the estimation of surgery durations exceeds the scope of this literature review, as mentioned in the introduction of this chapter, we do not elaborate on this issue.

2.8 Applicability of research

Many researchers provide, next to the development of a model or a formulation, a thorough testing phase in which they illustrate the applicability of their research. Whether this applicability points at computational efficiency or at showing to what extent objectives may be realized, a substantial amount of data is desired. From Table 2.9, we notice that most of this data stems from reality. This evolution is noteworthy and results from the improved hospital information systems from which data can be easily extracted.

Unfortunately, the testing of procedures or tools based on real data does not imply that they finally get implemented in practice. Although Lagergren [163] indicates that this lack of implementation in the health services seems to have improved considerably, it is hard to find statements in contributions that explicitly confirm the implementation and use of the procedures in practice (see [27, 28, 131] for an example). It is also unclear what *use in practice* actually entails. Applying a case mix model once every 2 years clearly results in a different degree of implementation than the daily application of a surgery sequencing algorithm. A clear comparison of manuscripts on this aspect is hence not straightforward. Moreover, even if the implementation of the research can be assumed, authors hardly provide details on the implementation process. The causes of failure or success throughout the implementation phase, however, may be of great value to the research community. In Section 2.4, we already pointed at the leading role surgeons may play in the acceptance or refusal of new operating room planning and scheduling procedures. One other possible determinant for the current poor implementation rate relates to the hospital management. When the implementation of the algorithms and procedures is not directly accompanied by significant short term financial gains (or equivalently, a strong reduction in operating costs), management is reluctant to change procedures or stimulate further investments in research (see Chapter 6). The set of manuscripts that is discussed in this literature review, however, indicates that an adequate application of planning and scheduling techniques may trigger improvements for each stakeholder in the operating theater. In order to determine the true value of the developed operations management techniques, an integrated view should be applied. Furthermore, the provision of additional information on the behavioral factors that coincide with a procedure's implementation has to be encouraged. We have to remark, however, that increasing the implementation rate does not only depend on the efforts of the scientific community. Possibly, practitioners lack some kind of awareness of the power of operations management techniques. Therefore, educational applications should be developed to introduce planning and scheduling concepts to the managers of the future. Hans and Nieberg [126] recently report on an educational tool that specifically focuses on the management of the operating room. Each player manages a virtual operating theater and has to decide on, for instance, the capacity of operating rooms, the allocation of the available operating room time to medical disciplines or the scheduling of individual patients. Throughout the game, players are introduced to operations management principles applied to health care and learn from the consequences of their planning and scheduling decisions.

A result of the poor implementation rate is that a substantial gap may exist between theory and practice. Only limited research is performed to quantify this gap and to indicate what expertise is currently in use in hospitals. Using a survey, Sieber and Leibundgut [250] recently noticed that the current state of operating room management in Switzerland is far from excellent. It is somehow contradictory to see that in a domain as practical as operating room planning and scheduling, so little research seems to be effectively applied. In Chapter 4, we apply a survey to identify the operating room planning and scheduling practices in Flanders.

2.9 Conclusion

In this chapter, we reviewed manuscripts on operating room planning and scheduling that have appeared recently. We analyzed the contributions on various levels, which we referred to as fields. Within each field, we highlighted the most important trends and we illustrated important concepts through the citation of key references. Since each discussion is accompanied by a detailed table, which provides even more information than is addressed in the text, readers may easily identify manuscripts that have specific features in common. They furthermore allow to track specific contributions over the different fields and visually indicate what area of research is well addressed or should be subject to future research.

In short, we noticed that most of the research that appeared in or after 2000 is directed to the planning and scheduling of elective patients. The study of issues related to the waiting time of various stakeholders and the utilization of resources seems to be well addressed. Most of the researchers analyze and/or solve their problem, which is frequently formulated at the patient level, by means of mathematical programming methods or simulation. This results in a steady amount of both optimization approaches and scenario analyses. Although the operating theater can be linked with an upstream and downstream process, such integration only occurs for about half of the contributions. Operating room planning and scheduling problems are furthermore studied both in a deterministic setting and a stochastic setting. Although the incorporation of uncertainty is more realistic, a lot of researchers prefer the deterministic approach due to the computational complexity. Unfortunately, bridging the gap with reality and implementing the advances in practice seems to be very difficult and should be further addressed in the future.

Chapter 3

Classification scheme

As shown by the literature review of Chapter 2, the increasing interest in the domain of operating room planning and scheduling leads to a proliferation of problem types. The statement and the scope of the problems, discussed in the papers, are often unclear. As such, the effort of researchers to verify whether the particular problem is really interesting with respect to their own research purposes, increases. The introduction of an adequate scheme to classify the contributions on operating room planning and scheduling, which constitutes the subject of this chapter, may present a first step to structure and clarify forthcoming research in this domain.

One major concern in the development of classification schemes is the trade-off between information and notation. Providing a lot of information easily results in an overcomplicated notation. In our opinion, the goal of a classification scheme is to provide as much (meaningful) information as possible while maintaining a simple and brief notation. On the one hand, classification schemes hence have to incorporate a sufficient amount of detail to represent a clarifying framework or taxonomy, while they have to offer a sufficient degree of freedom to the user to specify the problem setting, on the other hand. Therefore, classification schemes should be meaningful, brief and flexible as the acceptance of the scheme by the scientific community is otherwise doubtful. Moreover, classification schemes should exclude ambiguity as it is not allowed to state multiple notations for one particular problem.

The introduction of descriptive fields may assist in the development of classification schemes, especially since this structuring approach already proved to be useful in other scheduling and planning domains, such as machine scheduling or project scheduling. The classification scheme that was introduced for machine scheduling problems is composed of three fields α, β and γ [29, 30, 117]. The first field α describes the machine environment (e.g. job shop, flow shop). The second field β comprises the task and resource characteristics (e.g. task processing times, deadlines). The third and final field γ provides information on the performance measures of interest. A similar structure can be identified to classify project scheduling problems. Demeulemeester and Herroelen [51] generalize the machine scheduling classification scheme and similarly describe three fields. In their scheme, the fields α, β and γ respectively describe the problem's resource characteristics, activity characteristics and performance measures. Both classification schemes specify for each field a number of *parameters* which can take multiple values. These values are referred to as *elements* and provide the actual information. In this chapter, we adopt this terminology.

The literature review of Chapter 2 provides a head start for the development of an operating room planning and scheduling classification scheme as it is already structured using descriptive fields. However, building a scheme that consists of 7 fields violates the requirement to be brief. Therefore, we need to filter and aggregate the content of Chapter 2 and retain only that information that is highly relevant for a clear problem description (see Section 3.1). In Section 3.2, we elaborate on each retained field and introduce the necessary set of parameters and elements. An optional further specification of the elements is provided when applicable. Section 3.3 clarifies the use of delimiters in the classification notation, whereas Section 3.4 provides some examples to illustrate the applicability of the scheme. A summary of the chapter's classification approach is finally stated in Section 3.5.

3.1 Field reduction

It should be noted that not every field of the literature review clarifies the problem setting as such. Therefore, the main guideline to decide whether a field should take part in the classification scheme, is to identify if it provides information on the problem statement instead of the problem analysis, evaluation or solution. In other words, it does not matter for a correct understanding of the operating room planning or scheduling *problem* whether real or theoretic data is used to validate the algorithmic solution quality, whether the algorithm is based on dynamic or linear programming, whether the problem is solved to optimality or analyzed by what-if scenarios. As a consequence, including the fields concerning the type of analysis (see Section 2.5), the solution or evaluation techniques (see Section 2.6) or the applicability of the research (see Section 2.8) will not improve the comprehension of the problem statement and may hence be excluded from the classification scheme.

Although the removed fields do not directly address the statement of the planning or scheduling problem, this does not imply that they are not valuable to the researcher. Moreover, since the specification of the operating room planning or scheduling problem is actually a main characteristic of a paper, one may argue why the scope of the classification scheme is not enlarged from problem classification to paper classification. As long as a single problem is addressed in a paper, this reasoning seems to be valid. However, how should we classify a single paper in which multiple problems are formulated, each solved or analyzed with other techniques and other types of data? In our opinion, classifying problems instead of papers is much more transparent and hence preferred to structure future research.

Reducing the number of descriptive fields by 3 implies that 4 major fields suffice to provide a problem-based operating room planning and scheduling classification scheme. In particular, we should incorporate information on the patient characteristics, the decision delineation, the uncertainty and the performance measures, as discussed in the next section.

3.2 Fields, parameters and elements

Similar to machine scheduling and project scheduling, we refer to the 4 fields using Greek symbols. The first field, α, deals with the class of patients that is addressed in the planning or scheduling problem. The second field, β, indicates what type of decision is addressed and to whom it applies. Furthermore, it provides information on the degree of operating room integration with other facilities in the hospital. The third field, γ, indicates to what extent uncertainty is explicitly dealt with in the problem setting. The fourth field, δ, finally represents the performance measures of interest. In the next subsections, we discuss each field in more detail. For each element or further specification, we add in brackets the abbreviation that will be used in the classification notation.

3.2.1 Field α: Patient characteristics

The first field, α, provides information on the types of patients that are addressed in the problem and hence coincides with Section 2.2 of the literature review. In particular, the field comprises only one parameter ($\alpha = \{\alpha_1\}$) with 4 elements, i.e. the parameter can take 4 different values, to delineate the patient characteristics.

- α_1: *Patient class*: Patients can be treated as inpatients *(in)*, outpatients *(out)*, urgencies *(ur)* or emergencies *(em)*. We refer to Section 2.2 for a definition of the elements. It should be noted that multiple patient types can be addressed in a single planning or scheduling problem.

3.2.2 Field β: Delineation of the decision

The introduction of the second field, β, enables researchers to indicate the kind of decisions that have to be taken in their operating room planning and scheduling problem. The field consists of 3 parameters ($\beta = \{\beta_1, \beta_2, \beta_3\}$). It provides information that is discussed in Section 2.4 of the literature review and deals with the following questions: who or what is the subject of the decision (β_1), what type of decision is addressed (β_2) and to what extent is the operating room studied in an integrated way (β_3)?

- β_1: *Subject of decision*: This parameter indicates *to whom* the particular decisions apply. We distinguish between 4 elements: medical disciplines *(disc)*, surgeons *(surg)*, patients *(pat)* or other subjects *(other)*, such as hospitals. We refer to Section 2.4 for a definition of the elements. It should be noted that multiple subjects or levels can be addressed in a single problem.

- β_2: *Type of decision*: What decision has to be made? We distinguish between 5 elements: decisions related to the assignment of a date *(date)*, a time indication *(time)*, an operating room *(room)*, capacity *(cap)*, or other decisions *(other)*. We refer to Section 2.4 for a description of the elements. It should be noted that multiple decision types can be addressed in a single problem.

- β_3: *Degree of integration*: Does the problem integrate the operating room with other facilities or units in the hospital? We introduce 2 elements: either the problem studies the operating room in an isolated way *(iso)*, or it integrates the operating room with upstream and/or downstream facilities *(int)*. When integration occurs, we allow for an optional further specification of the linked facilities. We differentiate between the post-anesthesia care unit *(PACU)*, the intensive care unit *(ICU)*, the hospital wards *(ward)* or other facilities *(other)*. We refer to Section 2.4 for a description of the elements.

3.2.3 Field γ: Uncertainty incorporation

Field γ consists of a single parameter ($\gamma = \{\gamma_1\}$) and indicates the extent of stochasticity that is explicitly dealt with in the problem setting.

- γ_1: *Extent of stochasticity*: To what extent does the problem explicitly incorporate uncertainty in its description? We identify 2 elements: the problem can either be deterministic *(det)* in nature, or stochastic *(stoch)*. We allow for an optional further specification of stochasticity in arrival uncertainty *(arr)*, duration uncertainty *(dur)* or other kinds of uncertainty *(other)*. We refer to Section 2.7 for a description of the elements.

3.2.4 Field δ: Performance measures

The fourth and final field (δ) that is required to classify operating room planning and scheduling problems relates to the performance measures or the objectives that are addressed. In particular, two parameters are identified ($\delta = \{\delta_1, \delta_2\}$): the first parameter ($\delta_1$) is related to the question whether the problem addresses multiple objectives, whereas the second parameter (δ_2) lists the types of performance criteria that are incorporated.

- δ_1: *Objective scope*: Does the problem incorporate a single criterion *(single)* or multiple criteria *(multi)* to evaluate solutions to the operating room planning or scheduling problem?

- δ_2: *Performance measures*: What kind of performance measures are stated or evaluated in the problem? We distinguish between performance criteria that relate to waiting time *(wait)*, throughput *(through)*, utilization *(util)*, leveling *(level)*, makespan *(C_{max})*, deferrals or refusals *(defer)*, financial issues *(fin)*, preferences *(pref)* or other criteria *(other)*. We allow for an optional further specification of utilization as frequently a distinction is observed between overutilization *(over)* or underutilization *(under)*. We refer to Section 2.3 for a description of the elements. It should be noted that multiple criteria can be addressed in a single problem.

Note that multiple criteria may be addressed under a single type of performance measure. In other words, there is no guarantee that the occurrence of a single type of performance measure also implies that a single objective is used to evaluate procedures or systems. Think, for instance, of a setting in which $\delta_1 = multi$ and $\delta_2 = level$. This statement would apply when the problem at hand deals with the leveling of the beds in the PACU and the leveling of the workload in the operating room.

3.3 Delimiters

In order to structure the notation of problems using the classification scheme, a set of delimiters has to be introduced. This is necessary to keep track of the

Table 3.1: Summary of the use of delimiters in the classification scheme

Delimiter	Function	Example
$\vert$	Field delimiter	$\alpha\vert\beta\vert\gamma\vert\delta$
;	Parameter delimiter	$\alpha\vert\beta\vert\gamma\vert\delta_1;\delta_2$
,	Element delimiter	$\alpha\vert\beta\vert\gamma\vert\delta_1; wait, util$
()	Delimiter for further specification of an element	$\alpha\vert\beta\vert\gamma\vert\delta_1; wait, util(over)$
-	Delimiting multiple statements within a further specification	$\alpha\vert\beta\vert\gamma\vert\delta_1; wait, util(under-over)$
{}	Delimiting a group of coherent statements	$\alpha\vert\{\beta_1;\beta_2;\beta_3\}\{\beta_1;\beta_2;\beta_3\}\vert\gamma\vert\delta$

field, parameter, element and further specification hierarchy. An overview of the delimiters is depicted in Table 3.1. In the next paragraphs, we clarify their use by introducing the delimiters step by step.

First, we have to separate the fields from each other. As mentioned in Section 3.2, the four fields are referred to as α, β, γ and δ. As indicated in Table 3.1, we separate these fields using a "|" symbol: $\alpha|\beta|\gamma|\delta$.

Second, we can replace the general representation of the fields by their constituting parameters. Since multiple parameters have to be specified for fields β and δ, we also need a delimiter here. Table 3.1 shows to delimit these parameters using a ";" symbol: $\alpha_1|\beta_1;\beta_2;\beta_3|\gamma_1|\delta_1;\delta_2$.

Third, we have to substitute the parameters by the corresponding element or value that describes the operating room planning and scheduling problem. As mentioned in the introduction of the chapter, the elements actually provide the real information. Again, multiple elements may be specified for one specific parameter, which also urges the use of a delimiter, namely a "," symbol, in this step. Note that for each parameter at least one element has to be chosen. We illustrate the application of the delimiter for field α: $in, out|\beta_1; \beta_2; \beta_3|\gamma_1|\delta_1; \delta_2$. This example would imply that the planning or scheduling problem deals with both inpatients and outpatients, i.e. elective patient scheduling.

In Section 3.2, we stated that multiple elements may be optionally further specified so that they also have to be integrated in the classification notation. Each further specification of an element will appear in brackets, as shown in Table 3.1. Similarly to the previous paragraph, though, multiple specifications may be introduced in the notation for a single element. Therefore, we introduce a "$-$" as delimiting symbol. We illustrate this structuring approach for field γ: $\alpha_1|\beta_1; \beta_2; \beta_3|stoch(arr - dur)|\delta_1; \delta_2$. This notation indicates that the problem at hand explicitly deals with uncertainty, in particular both arrival uncertainty and duration uncertainty.

It may occur that multiple subjects are addressed in the same operating room planning or scheduling problem. Think, for example, of the case in which patients have to be assigned to surgeons and a surgery date has to be assigned to the patients. When these decisions are dealt with in a sequential way, the classification scheme, as it is explained up to now, can be applied and would result in two problem statements, namely $\alpha|$ $surg; other; \beta_3$ $|\gamma|\delta$ and $\alpha|$ $pat; date; \beta_3$ $|\gamma|\delta$. However, when both decisions are studied simultaneously, the single problem statement would equal $\alpha|$ $surg, pat; other, date; \beta_3$ $|\gamma|\delta$. As such, we cannot identify the precise relation between the elements of parameter β_1 and β_2. Therefore, we introduce a final delimiter "$\{\}$" to group statements that belong together. We only apply the delimiter when ambiguity may occur. With respect to the example, we hence adapt the statement as follows: $\alpha|$ $\{surg; other; \beta_3\}\{pat; date; \beta_3\}$ $|\gamma|\delta$.

3.4 Examples

In this section, we illustrate the applicability of the operating room planning and scheduling classification scheme to various problems that are already studied in the literature. We refer to the literature review of Chapter

2 for an analysis of the papers that we classify in this section. For some papers, we are unable to fill out the appropriate set of elements for some parameters. This is not because the sets of elements for the parameters are inadequate, but because the papers do not include any specific information on the particular parameters. This is often the case with respect to parameter α_1 that describes the patient characteristics (see Section 5.1). Therefore, we introduce the abbreviation NS (not specified). It should be clear that if researchers systematically apply the proposed classification scheme in the future, such unclear statements will be eliminated.

Figure 3.1 may assist in the correct determination of a problem's classification notation, as it recapitulates the fields, parameters, elements and further specifications that were introduced throughout this chapter. Note that the abbreviations of the elements are quite descriptive instead of mathematical, which should be beneficial for an easy comprehension of the classification notation. This comprehension should be furthermore improved by the absence of blank entries in the scheme (i.e. for each parameter, at least one element has to be specified). Although we believe that this policy increases the clarity of the scheme, it may lengthen the problem's notation.

The problem that is studied by Adan and Vissers [2] is classified as $in, out \mid pat; date, cap; int(ICU - ward) \mid det \mid multi; util(over - under)$. From this notation, a lot of information can be deduced. The problem takes both inpatients and outpatients into account. It is formulated in terms of patients or patient types for whom capacity has to be determined and a day or date has to be assigned. These decisions seem to have consequences for other facilities, in particular the wards and the ICU, as the operating room is studied in an integrated way. The problem does not explicitly incorporate uncertainty and is hence deterministic in nature. Multiple objectives are taken into account that are related to the utilization of resources. In the evaluation of the utilization levels, the authors even seem to make a differentiation between overutilization and underutilization.

Dexter et al. [60] examine the following problem: $out \mid surg; cap; int(ICU -$

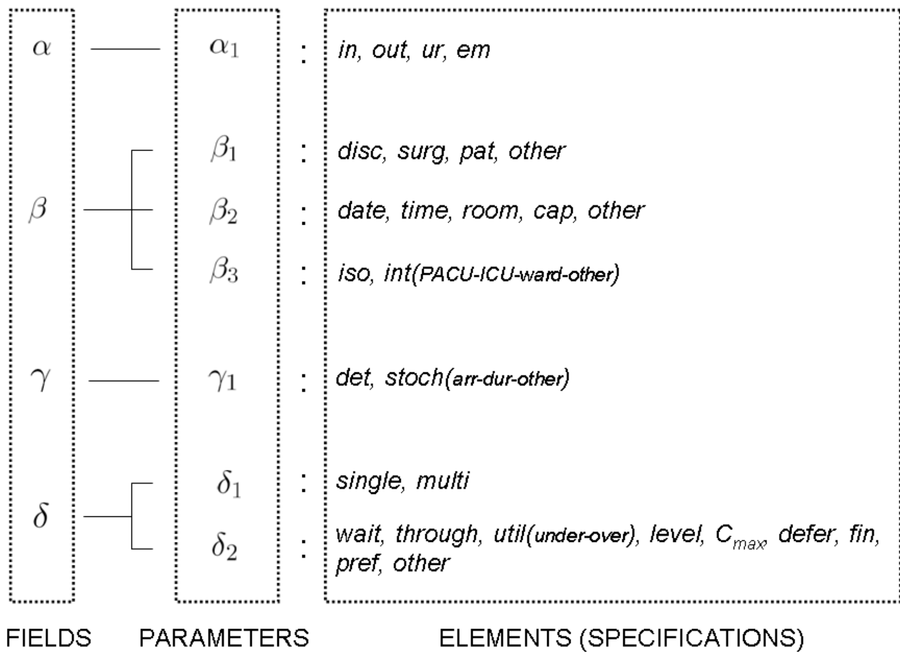

Figure 3.1: Overview of the fields, parameters, elements and further specifications that constitute a classification scheme for operating room planning and scheduling problems

$ward) \mid det \mid single; fin$. In particular, they studied the financial implications of changing the assignment of operating room capacity, which is reserved for outpatient surgery, to surgeons. They apply a deterministic view but link the operating room to the ICU and the hospital wards.

The operating room scheduling problem that is presented by Beliën and Demeulemeester [14] is summarized by the classification scheme as follows: $in \mid disc; date, time; int(ward) \mid stoch(arr - dur) \mid single; level$. The authors study the impact of changing the date and the time of operating room inpatient sessions, assigned to medical disciplines, on the demand of a single resource which they try to level. The changes in the operating room schedule seem to have repercussions on the hospital wards and this relation is incorporated in the model. Both arrival uncertainty and duration uncertainty is embedded in the model.

The classification notation of the problem that is addressed by Van Houdenhoven et al. [276] can be written as follows: $in \mid pat; date, room, cap; iso \mid stoch(dur) \mid multi; util, other$. Based on this classification, we may assume that this research deals with the assignment of a date, a room and capacity to inpatients. The authors incorporate duration stochasticity. Since their focus is restricted to an isolated set of operating rooms, these durations denote the surgery durations. The various assignments are compared with respect to the operating room utilization and some other criterion, namely the number of freed operating rooms.

In Chapter 5, we come back to the classification scheme and apply it to the operating room scheduling problem that originated at the day-care center of the UZ Leuven Campus Gasthuisberg (see Section 5.2) and to the literature that is related to this topic (see Section 5.1).

3.5 Conclusion

In this chapter, we introduced a scheme to classify the research on operating room planning and scheduling approaches on the basis of descriptive fields. In particular, we restricted the focus to the classification of operating room planning and scheduling *problems*. From the original 7 fields that were discussed in Chapter 2, 4 were retained for the classification scheme (α, β, γ and δ). In short, the classification scheme allows to provide information on the patient characteristics (α), on the type and the subject of the decision that needs to be addressed in the problem and the according degree of operating room integration (β), on the explicit incorporation of uncertainty (γ) and on the particular set of performance criteria (δ). Each field is further detailed using parameters, elements and optional further specifications. By means of some examples, we illustrated that this classification approach satisfies important goals, namely clarity, brevity, flexibility and unambiguity. As such, we hope to structure forthcoming research in the domain of operating room planning and scheduling. A major improvement would already be achieved if authors agree to think about the fit between their research and the information provided by the fields while writing down their problem description. It would, for instance, strongly reduce the number of “not specified” or blank entries in Table 2.1 in Chapter 2 (patient characteristics).

Chapter 4

A survey on operating room planning and scheduling in Flanders

In order to develop effective planning and scheduling procedures, a thorough knowledge about the setting in which these methodologies have to be applied is indispensable. Moreover, the availability of valuable insights, provided by the scientific community, does not guarantee that they are implemented and used in practice, which eventually may result in a substantial gap between theory and practice. In this chapter, we examine the current practice of the Flemish hospitals with respect to the planning and scheduling of their operating theaters and try to evaluate the above research questions by means of a survey that was conducted in cooperation with Jessie Van der Hoeven [273]. Note that this survey takes part in a larger programme in which Flemish hospitals were also questioned about appointment scheduling [193] and nurse rostering approaches [281].

The literature provides only few studies in which the current practice of operating room management is described and evaluated in detail. Sieber and Leibundgut [250], for instance, surveyed the public hospitals in Switzerland on information about the structure and organization of the operating rooms as well as their opinions and expectations about the management (35 respondents). Although the respondents express their awareness of the importance of an adequate information system, results indicate only poor operating room management performance. The authors furthermore provide best practice guidelines as a helpful tool for the hospital management to improve their current practice. Gemmel and Bourgonjon [108] also report on the use of a questionnaire to evaluate the management of the operating theater. The results of a survey in Flanders (61 respondents) were used to illustrate some general managerial insights with respect to the planning and scheduling of surgical patients. Since our target population corresponds to theirs (see Section 4.1), we exploit in Section 4.3 the opportunity to examine whether Flanders' practices with respect to the planning and scheduling of operating rooms have evolved over time.

The remainder of this chapter is structured as follows. In Section 4.1, we discuss the design of the survey and delineate the target population. Section 4.2 provides information on the response rate of the survey and indicates its most important results, both with respect to the development of surgery schedules and their corresponding realization in practice. Section 4.3 provides a discussion on the (mis)match between the current practice of operating room planning and scheduling in Flanders and the recent developments that are addressed in the scientific literature. As mentioned in the previous paragraph, we furthermore briefly indicate whether the results of Gemmel and Bourgonjon [108] differ from the recent findings. A brief conclusion of this chapter is finally stated in Section 4.4.

4.1 Methods

Starting from the set of Belgian hospitals provided by the Belgian Hospital Association [12] in 2006, we restricted the target population of the survey to those hospitals that are situated in the Flemish Region. Note that the public health affairs in Belgium are currently not addressed at the federal level. As we only focus on the Dutch-speaking part of Belgium, linguistic difficulties are furthermore excluded. Our search eventually resulted in 95 hospitals (both private and public) that are equipped with a functional operating room department. All hospitals received by the end of November 2006 an electronic questionnaire by e-mail. We preferred this electronic format to the regular postal services as it allows for an automated registration of the answers in a spreadsheet application. Moreover, it is a quick, cost-effective and user-friendly method. In order to increase the response rate, reminders were sent by e-mail approximately one month after the initial submission. Unlike the first e-mail, which was sent to the general information desk of the hospitals, this second e-mail was directed to the employee responsible for the planning of the operating theater as detailed contact information was retrieved from a preceding telephone call. We ended the registration of the responses by the beginning of March 2007.

The questionnaire was kept as brief as possible (a printout of about 7 *A4* pages) and covered, next to general questions about the institution, issues related to the operating room planning and scheduling process of both the elective and the non-elective surgeries. For most of the questions, which are either quantitative or qualitative in nature, we suggested a list of possible answers. Check boxes, radio buttons or edit controls were provided to facilitate the decision process or to rank the alternatives. Furthermore, respondents were able to specify their answer or provide a new entry when no match in the suggested list could be found. The participating hospitals received a summary of the results afterwards.

4.2 Results

In this section we present the results of the survey. We first elaborate on the response rate and check whether the composition of the represented hospitals is well balanced. Second, we highlight and visualize some of the most interesting findings of the questionnaire, both with respect to the development of the surgery schedule and its actual realization.

4.2.1 Response rate

The first mailing resulted in 39 responses, whereas the second one added another 13 responses. This total of 52 responses implies a response rate of 55%, which is close to the 58% that was encountered by Gemmel and Bourgonjon [108]. About 62% of the respondents clearly indicate to be the head nurse of the operating theater. Since hospitals were free to choose the profile of their respondent, it seems that the function of head nurse is the most appropriate to assess operating room planning and scheduling practices in Flanders. This observation deviates from the view expressed by Sieber and Leibundgut [250], as anesthesiologists were addressed in their survey.

We added Figure 4.1 to depict whether the entire population of hospitals in Flanders is well represented by the 52 hospitals of the response set. In Figure 4.1 (a), we categorize the hospitals in intervals according to the number of available operating rooms. About 85% of the Flemish hospitals has less than 10 operating rooms at their disposal, while this capacity corresponds to about 80% of the hospitals in the response set. For each interval, we notice only slight deviations (at most 3 percentage points) between the percentage of hospitals in Flanders and the percentage of hospitals in the response set. This implies that with respect to the number of operating rooms, the response set is quite representative for Flanders in its entirety. A similar reasoning applies to a categorization of the hospitals based on the available number of hospital beds, as depicted in Figure 4.1 (b). From this figure we see that the most important category of hospitals in Flanders consists of hospitals with a capacity of beds between 151 and 300 (46%). In the response set, about 50% of the hospitals fall into this category. The largest deviation in percentage points between the response set and the entire population of hospitals exists for hospitals with a bed capacity of maximum 150 beds. However, since this deviation is barely equal to 6 percentage points, we consider the bias to be negligible and hence conclude that the response set is also with respect to the hospital bed capacity representative for Flanders.

We asked the hospitals for the number of surgeries that they have performed in 2005. Most of the hospitals in the response set performed less than 10000 surgeries (48%). About 32% performed between 10000 and 20000 surgeries. The remaining hospitals accounted for more than 20000 surgeries (11%) or did not answer the question (9%). While 41% of the hospitals are satisfied with the current operating room capacity, about 59% indicate to expand

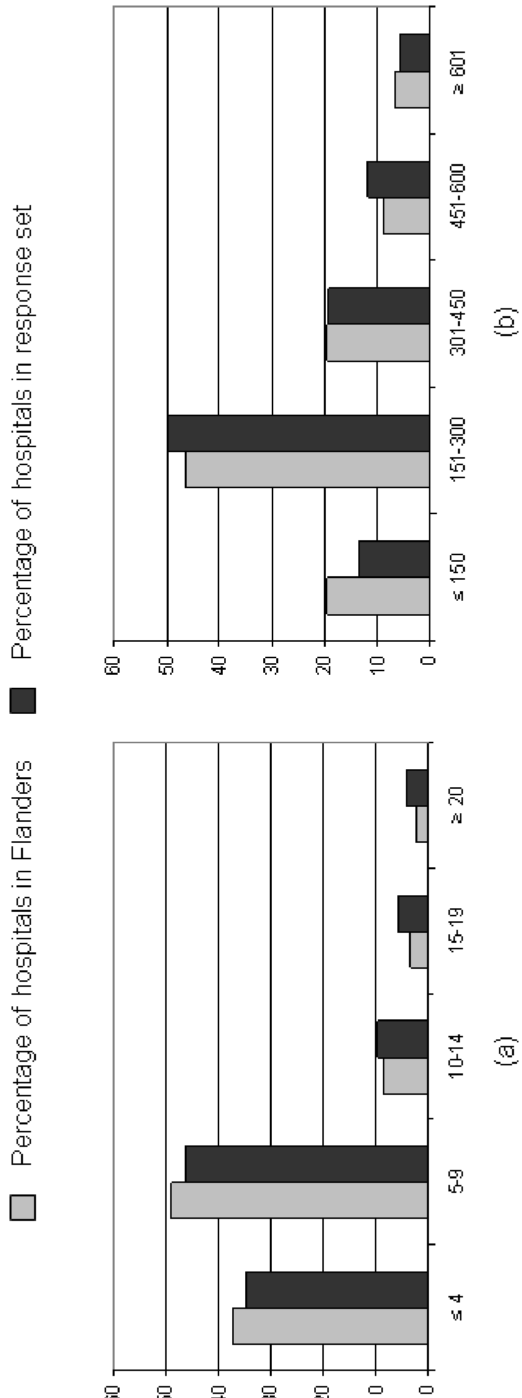

Figure 4.1: Indicating whether the set of respondents is representative for Flanders with respect to (a) the number of operating rooms and (b) the number of hospital beds

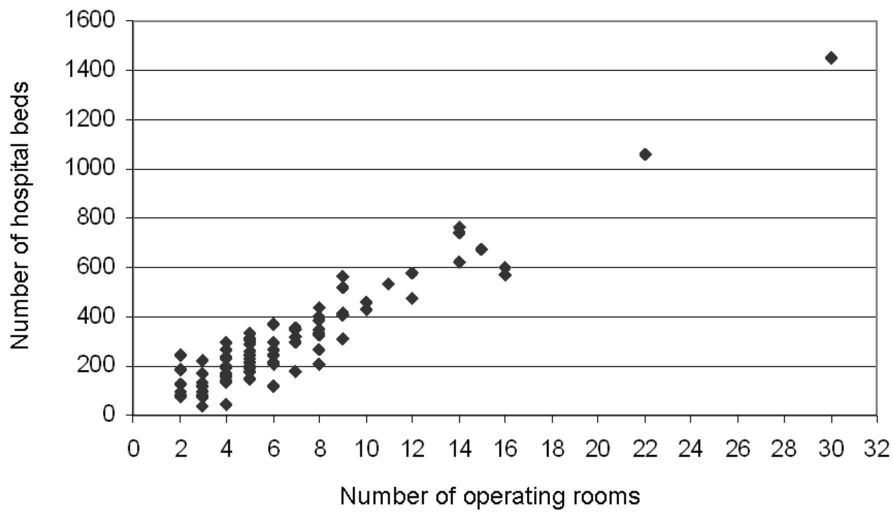

Figure 4.2: Visualizing the linear relation between the number of operating rooms and the number of hospital beds

their capacity in the future. Two major reasons were mentioned to justify this expansion. Either the operating room capacity is insufficient to satisfy the current demand for surgeries (48%), or it is insufficient to cope with the future (expected) demand for surgeries (30%). By 2020, Etzioni et al. [89] predict significant increases in the workload of surgical specialties in the United States of up to 47% as a result of the aging population, although these increases may vary widely by specialty. Other reasons to justify the operating room capacity expansions (22%) are rather strategic in nature, such as the construction of a freestanding ambulatory center. Note that an increase in the number of operating rooms will probably trigger a linear increase in the number of hospital beds too, as the correlation coefficient of these variables, based on the entire population of hospitals in Flanders, is equal to 0.95. Alternatively stated, the scatter plot depicted in Figure 4.2 shows that there is a strong linear and positive relation in Flanders between the number of operating rooms and the number of hospital beds.

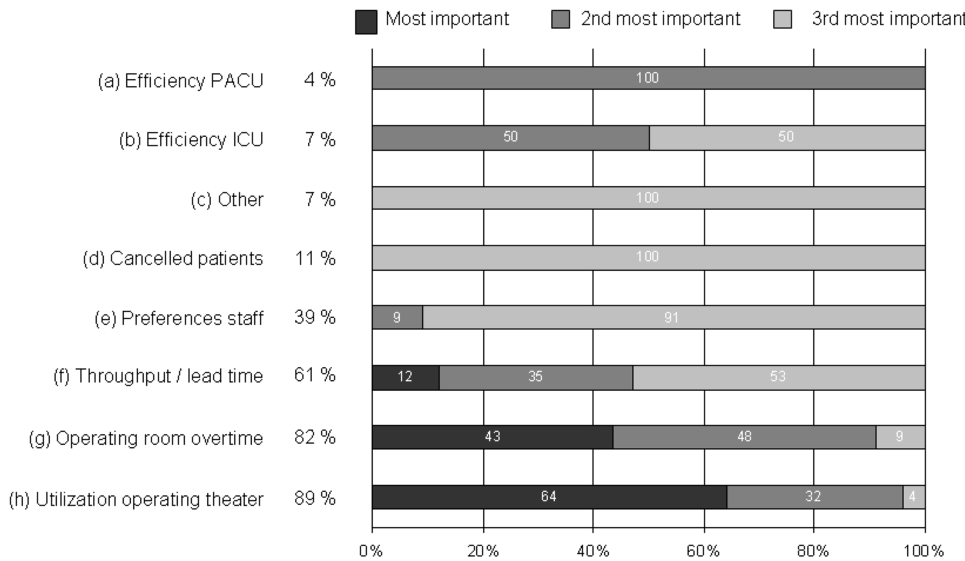

Figure 4.3: Importance of various objectives applied to the planning and scheduling of the operating theater

4.2.2 Surgery schedule development

Various objectives may be addressed during the development of the surgery schedule. We asked the respondents to select from a predefined list three objectives that are, in their opinion, important. They furthermore had to sequence their three important objectives according to their preferences (important, more and most important). The results are summarized in Figure 4.3. About 89% of the respondents indexed the high utilization of the operating theater (h) as important, which is the highest score that was obtained over all the objectives. The avoidance of overtime in the operating rooms (g) also seems to be highly important (82%). At the other end, constructing surgery schedules in such a way that the post-anesthesia care unit (a) or the intensive care unit (b) can be managed efficiently, does not seem to be of major interest to the respondents (respectively 4% and 7%). Only few respondents specified some other objective, i.e. an objective that was not suggested in the predefined list, to be important (7%). One such objective is, for instance, to maximize the ease of planning and scheduling. For each objective (a-h), Figure 4.3 also provides a horizontal bar in which we only focus on the set of respondents who indicated that the particular objective is important. More specifically, we indicate for that limited set of respondents who ranked the objective as the most important, the 2nd most important and the 3rd most important (expressed in percentage). Let's focus once more on the high utilization of the operating theater (h). We mentioned that 89% of the respondents indicated that this is an important objective. Although this percentage is very high, it would be less powerful if none of the respondents ranked this objective as the most important one. From Figure 4.3, we see that about 64% of these respondents indexed objective (h) as the most important, 32% as the 2nd most important and 4% as the 3rd most important. The interpretation of the horizontal bars should hence always be in the perspective of the percentage of respondents who indicated its importance, and vice versa.

Next to the decision about the objectives that have to be achieved, hospitals also have to think about the way to accommodate the demand for surgery properly. In particular, hospitals do not only have to decide on the amount of operating room time to assign to surgeons or disciplines, but also on the time or date. Results of the survey indicate that elective surgery is in general planned from Monday to Friday (78%). Only a few respondents clearly confirm to perform some elective surgery in the weekend (15%). The remaining 7% of the respondents provided a blank answer. Three major assignment policies are described in the literature [121, 219]. First, it is possible to reserve an amount of operating room time (blocks) solely for cases of specific surgeons or medical specialties. This system is often referred to as block scheduling. Second, operating room time assignments may occur according to an open scheduling policy. In this policy, no blocks are assigned in advance and cases are treated on a first come first served basis. Modified block scheduling represents the third assignment policy. This system is either a combination of the preceding policies or a variant of the block scheduling policy in which unused but reserved time is released at an agreed-upon time before surgery. With respect to the response set, only a minority of the hospitals in Flanders currently applies block scheduling (4%) or open scheduling (2%). Most hospitals (94%) favor a modified block scheduling policy. All hospitals in this large set confirmed their use of a specific release time to free unused block capacity. About 66% indicated to release operating room time less than 24 hours before the day of surgery. 16% have a release time that is between 24 and 48 hours before the day of surgery, while 18% indicate to release capacity more than 48 hours in advance. Since the required accommodation of operating rooms may differ between specialties, block scheduling or modified block scheduling seems to be inevitable to guarantee that the operating room is suitable for certain procedures. About 30% of the hospitals in the response set indicate that their operating rooms are capable of accommodating any surgery. The remaining 70% have a set of non-identical operating rooms. We asked this set of respondents to what extent operating rooms may differ. The results show that differences occur in size (69%), fixed equipment (50%) or other aspects (19%), such as the treatment of air flows or the proximity of inventory (logistics).

A popular way to schedule patients in such a way that the objectives of the hospital are achieved, is the use of simple priority rules. Since this list of rules is practically infinite, we asked the respondents to list some of the rules they try to incorporate. Not surprisingly, a variety of rules was obtained: schedule outpatient surgeries first, surgeries of children first, perform surgeries in the sequence they were added to the schedule, surgeries with the longest processing time first, surgeries with the shortest processing time first, group surgeries of the same type and perform them consecutively, latex allergy patients first, contaminated patients last, etc. We do not provide numerical results, as it is possible that hospitals actually use rules that they did not even mention in the survey. It should be clear that the priority rule which states that outpatient surgery is preferably performed before the surgeries of inpatients, applies to hospitals in which an amalgam of inpatients and outpatients is scheduled in the same operating room. About a quarter of the respondents (24%), however, try to separate day-care or outpatient surgery from inpatient surgery.

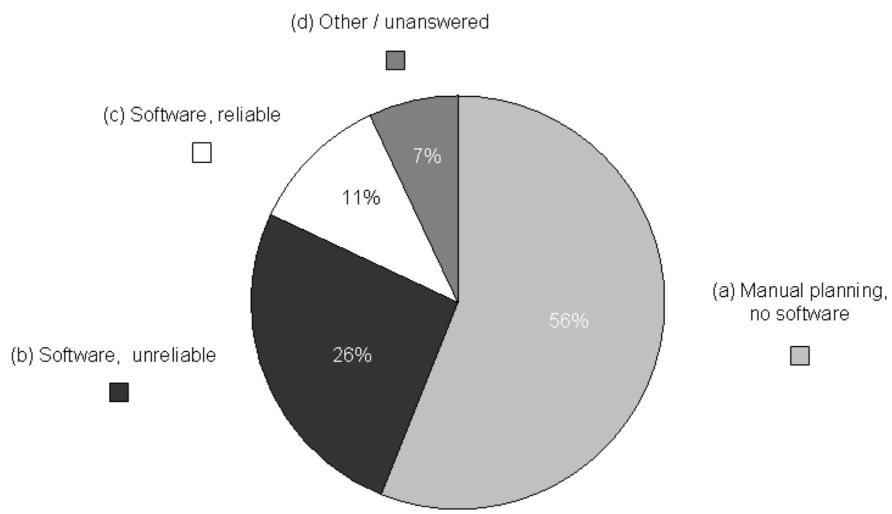

Figure 4.4: Visualizing the proportion of software use in the development of surgery schedules and its corresponding reliability

Achieving multiple objectives simultaneously is challenging as they are often interrelated and even conflicting. This implies that trade-offs may occur and priorities have to be stated while determining the operating room planning. Since this is a complicated task (see Section 4.3), software may assist in the planning phase. Figure 4.4 indicates the presence of information technology and optimization software in order to develop the surgery schedule. Surprisingly, more than half of the respondents (56%) still construct surgery schedules without software support, although this manual approach is time-intensive and often results in suboptimal schedules (a). However, the use of software is no guarantee to obtain a reliable schedule. About 26% of the respondents indicate that their software produces schedules that definitely have to be checked for errors (b). Only 11% of the respondents confirm that their software system is reliable and hence produces qualitative output (c).

The accuracy of surgery schedules obviously depends on the estimation of the surgery durations. We questioned the hospitals how these estimates are obtained and visualized the results in Figure 4.5. We identify three

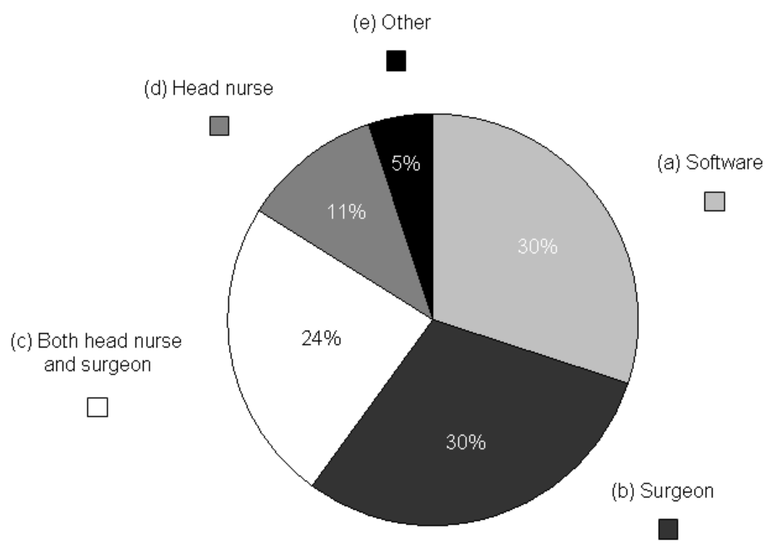

Figure 4.5: How to estimate the surgery durations

approaches that are almost equally applied in hospitals in order to estimate their surgery durations, namely by analyzing historical data using software (a, 30%), by the surgeon who will perform the specific surgery (b, 30%) or by a discussion between the head nurse and the surgeon (c, 24%). All hospitals that produce reliable surgery schedules using software also estimate their surgery durations using software. About 11% of the respondents report that the head nurse estimates the surgery durations (d). The remaining 5% represent alternative approaches (e), such as the combination of software support and personal experience to estimate the durations. Remark that about 65% of the hospitals do not rely on any software support.

4.2.3 Realization of the surgery schedule

The actual or realized surgery schedule often substantially deviates from the planned schedule. In Figure 4.6, we list 8 possible causes of a disrupted surgery schedule. We asked the respondents to exhaustively rank all the disruptions on their frequency of occurrence and classified them into three broad categories (frequently, sometimes, rarely). About 96% of the respon-

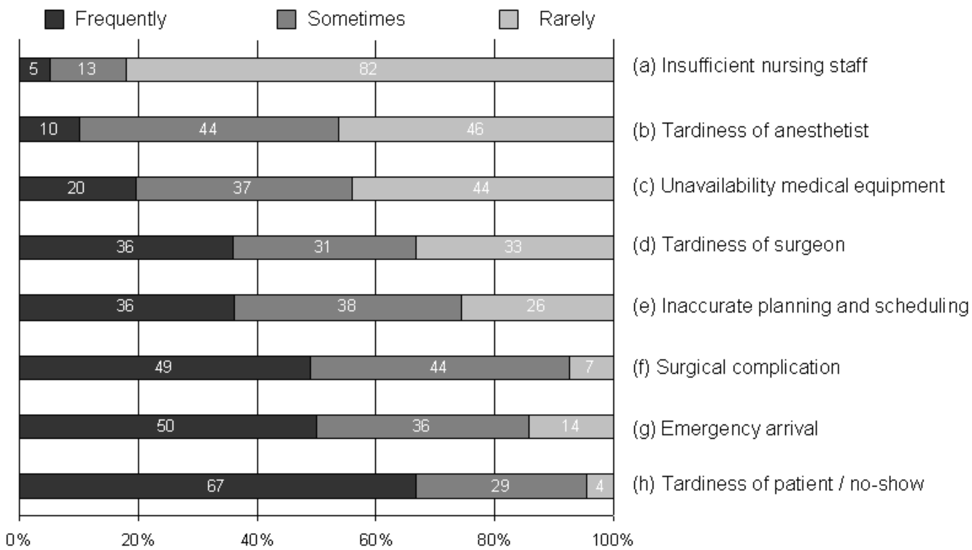

Figure 4.6: Overview and frequency of disruptions to the original surgery schedule

dents indicate to be at least sometimes confronted with the tardiness of a patient or a no-show (h). Such tardiness may result from, for instance, late arrivals of day-care patients or the lack of transporters to simultaneously provide patients to the operating rooms. We doubt, however, if this high percentage is substantially determined by the occurrence of no-shows, as only two hospitals could roughly indicate the yearly number of no-shows. For both hospitals, the percentage of no-shows was far less than 1% of their total surgical workload. Other important disruptions of the surgery schedule, for instance, stem from complications during surgery (f) or the arrival of non-elective patients (g), i.e. the class of patients for whom a surgery is unexpected and hence needs to be performed urgently. Ironically, the planning of the operating theater seems to be a substantial cause of its own disruption (e). On the contrary, hospitals in Flanders do not seem to cope with a lack of nursing staff to perform surgeries (a), nor with the tardiness of the anesthetist (b).

Hospitals may react to the negative consequences of the disruptions by in-

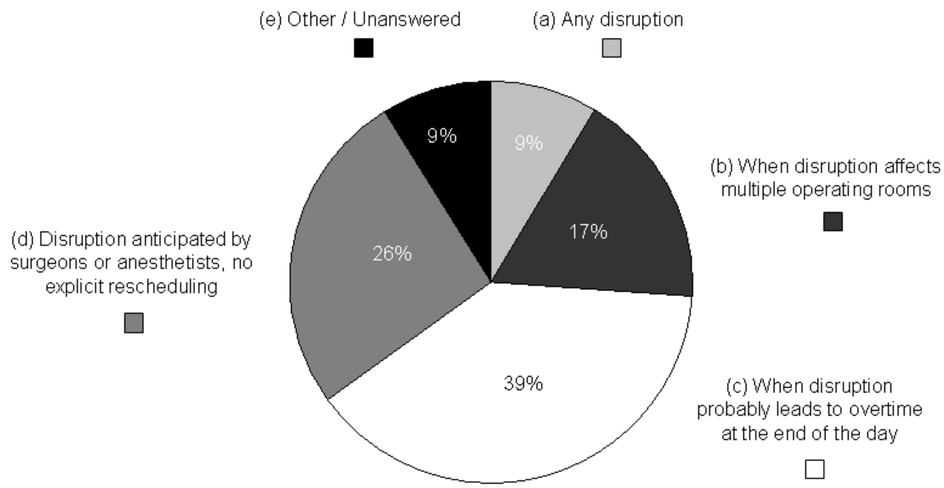

Figure 4.7: Degree of reactive scheduling in order to fix disrupted surgery schedules

ducing some necessary changes to the surgery schedule, such as swaps of surgeries between operating rooms. The threshold to introduce such reactive scheduling policies, though, differs between hospitals. Figure 4.7 shows that about 9% of the respondents reactively adapt their surgery schedule for any kind of disruption that takes place (a). About 17% of the respondents indicate to adjust the planning when the disruption tends to affect multiple operating rooms (b), whereas 39% change their planning when the disruption would lead to operating room overtime at the end of the surgery day (c). A substantial amount of respondents (26%) report that disruptions do not necessarily trigger explicit rescheduling, as the impact may be anticipated by the surgeons or the anesthetists (d).

Since the arrival of non-elective patients was expected to be an important cause of surgery schedule deviations, we surveyed the hospitals on the way they deal with such arrivals. Surprisingly, only 39% of the respondents register the occurrence of non-elective patients in their information system or database. 57% of the respondents, on the contrary, do not register non-elective arrivals. About 4% of the hospitals in the response set did not express their opinion about this question. When considering non-elective arrivals, we mentioned in Chapter 2 that a distinction can be made between emergent patients (emergencies) and urgent patients (urgencies) based on the responsiveness to the patient's arrival, i.e. the waiting time until the start of the surgery. The surgery of emergent patients has to be performed as soon as possible, whereas the urgent patients are sufficiently stable so that their surgery can possibly be postponed for a short period. With respect to the emergencies, 85% of the respondents report to perform the surgery in the operating room that is the first to be released (idle). Only 4% of the respondents indicate to intentionally reserve capacity for emergencies in advance. In particular, they provide one or multiple operating rooms that are only accessible to the emergent patients. Other opinions (4%) consist of, for instance, hospitals in which emergencies are performed in the first operating room that will be released, unless there is an operating room idle by accident (e.g. holiday of a surgeon). About 7% of the respondents left this question unanswered. With respect to the urgencies, two major practices are identified. Urgent surgeries are either performed at the end of the day, when the regular surgical program is finished (30%) or they are incorporated in the regular program of the appropriate discipline along the day (54%). The remaining part of the respondents (16%) indicates to combine both practices and makes a decision based on the specific discipline, surgeon, arrival time and surgery schedule or did not provide any opinion.

Occasionally, multiple non-elective patients arrive approximately at the same time so that priorities have to be stated. Dexter et al. [74] report on three strategies to sequence non-elective patients. First, it is possible to perform the surgeries based on medical priority. Second, cases can be performed in the order that they arrived. Third, one may perform the surgeries in the sequence that minimizes the average length of time both the surgeon and the patient have to wait. We asked the hospitals to rank these three policies according to their importance and visualized the outcome in Figure 4.8. A vast majority of respondents (86%) consider the medical aspects (a) as the most important feature to determine priorities. About 68% of the respondents indicate that the arrival sequence (b) is the less important factor that

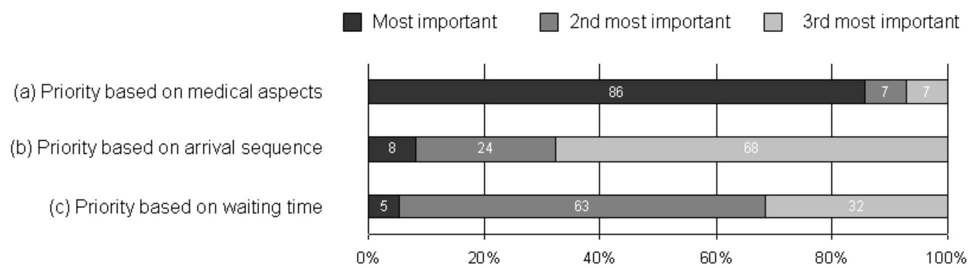

Figure 4.8: The importance of the medical aspect, arrival sequence and waiting time for setting priorities when multiple non-elective patients arrive simultaneously

should be considered for setting the priorities.

4.3 Discussion

We noticed that the outcome of this survey largely corresponds to the results that were obtained by Gemmel and Bourgonjon [108], as they also targeted the hospitals in the Flemish region for their questionnaire. We were able to compare certain aspects that were addressed in both surveys, such as the opinions about objectives, disruptions, estimation of durations, policies to accommodate urgencies and emergencies, open scheduling versus (modified) block scheduling or the occurrence of various priority rules. Except for small deviations in the percentages, both surveys point at comparable general insights. On the one hand, this similarity implies that the opinions and practices that relate to the planning and scheduling of the operating theater in Flanders are quite stable over time. On the other hand, this resemblance can be interpreted as a validation of the results. The design of our survey, however, does not entirely coincide with the one of Gemmel and Bourgonjon [108]. We also questioned the hospitals for issues related to, for instance, the algorithmic support for constructing the planning, expansion of the operating room capacity or the threshold for rescheduling due to disruptions. As we already mentioned in Section 4.1, we also wanted to keep the questionnaire as brief as possible to improve the response rate. Therefore, we did only reproduce a limited set of questions that were addressed in [108].

For the remainder of this section, we try to interpret some of the most interesting findings that result from the survey and evaluate how the scientific research efforts relate to the evolutions that we encountered in practice. With respect to the objectives, we indicated that hospitals mainly strive to achieve a high utilization of the operating theater while they want to minimize the risk of overtime. Moreover, they seem to pay thorough attention to both the improvement of throughput and lead times (i.e. waiting time) and they try to incorporate various preferences of the medical staff. This set of objectives seems to be well addressed in the literature (see Chapter 2). However, the application of planning and scheduling procedures does not only affect the performance criteria of the operating room itself, but also of its depending facilities, such as the post-anesthesia care unit, the intensive care unit or the hospital wards. Although the literature already provides many approaches that deal with these interrelated issues (e.g. [2], [226] or [244]), hospitals in Flanders do not yet seem to realize their importance. One reason for this void presumably lies in the inherent complexity that stems from the integration of the operating room with the other facilities in the hospital (see Chapter 2). Since the outcome of managerial measures in the operating room on these related facilities is difficult to predict for the human planner, advanced planning and scheduling techniques from the field of operations research and operations management are needed. We doubt if hospitals are currently aware of the power of these techniques, as more than half of the respondents clearly indicate to construct the surgery schedule manually. Without algorithmic support, evaluating the entire set of feasible solutions is virtually impossible and the opportunities to exploit the managerial power that stems from the operating theater are lost. In other words, optimization techniques may lead to an evaluation of a surgery schedule that is otherwise intractable for the human planner. In order to create this awareness amongst practitioners and to further improve the flexibility and user-friendliness of the emerging applications, a closer cooperation is needed between the hospitals and the scientific community, which should act as a pioneer in advanced technologies.

The quality of computerized and mathematical methods, though, depends on the way they are developed and used in an analysis. We can easily illustrate this proposition by means of an example in which we try to estimate the expected duration of a specific type of surgery. We focus on a procedure type that relates to the diseases of the skin and subcutaneous tissue (ICD-9 classification: 680-709) and include about 300 observations of actual and estimated durations (of surgeons) that are obtained from an academic hospital in Belgium. In particular, we are interested in the average deviation between the actual and the estimated surgery duration. This deviation equals 46 minutes when surgeons are allowed to estimate the surgery duration, whereas this deviation increases to 71 minutes when the estimated duration is set to the average based on the historical data. The estimation of the surgeons outperforms the mathematical average since the surgeons are able to differentiate even further between the patients of that particular class (e.g. based on age or slightly different intervention). However, when we group the patients with the same estimated duration (determined by the surgeon) and change for each subgroup the estimated duration to the corresponding mathematical average of the subgroup, we notice that the average deviation decreases to 35 minutes. It should thus be clear that the success of analytical and mathematical approaches depends on its implementation mode. We elaborate on this discussion in Chapter 6.

It is somehow disappointing to see that the hospitals in Flanders anticipate disruptions to the surgery schedule mainly in a reactive way, i.e. only dealing with problems when they actually occur. Instead, one could schedule in a proactive way and incorporate some expectations about disruptions during the construction of the surgery schedule. Think, for instance, about the arrival of non-elective patients. Although this type of disruption is definitively stochastic in nature, an expected daily amount of emergencies may be determined and an appropriate amount of operating room capacity may be reserved in advance for their treatment. Recall that only 4% of the respondents applied such a proactive scheduling policy. Although this spare capacity may be centralized in a single operating room, the responsiveness to emergencies is improved when this capacity is spread over the entire set of operating rooms [293]. One indispensable condition to generate proactive schedules, though, is the detailed registration of disruptions in a database. As indicated in Section 4.2.3, this prerequisite is currently lacking in the Flemish hospitals.

Today, the lack of nursing personnel is a widespread problem in hospitals. Although there seems to be a slight increase in supply, the shortage of nurses is still expected to be substantial in the future [5]. We already mentioned, however, that operating room scheduling may alleviate the peak demands for nursing personnel needed in the hospital wards, post-anesthesia care units or intensive care units. Surprisingly, the development of surgery schedules that achieve such leveling objectives does not seem to be a priority for the hospitals in Flanders (see Section 4.2.2). Moreover, the shortage of nurses does not seem to constitute a significant cause of disruptions to the surgery schedule (see Section 4.2.3). We believe that many respondents narrowed their view to the nursing personnel that assists during the surgery instead of including the nursing care that is needed immediately after the surgical act. Since medical staff and nursing personnel are costly resources, their use should definitively be planned in an efficient way.

Finally, we want to state a remark on the use and the design of surveys to gather information from the respondents. As already mentioned, we balanced the length of the survey (and hence the precision and the level of detail) with the expectations on the requested response rate. This resulted in a questionnaire that is rather brief, both in the number of questions raised and in the statement and preciseness of the questions themselves. As such, it is possible that the interpretation of questions differs amongst respondents. It is, for example, not unlikely that respondents indicate “what they would like to do” instead of “what they are currently doing”. Moreover, brief questionnaires in general lack the possibility to request additional information or opinions, which respondents may feel to express. Therefore, it would be appropriate to confront the hospitals with their answers (and the answers of their fellow hospitals) and discuss their meaning and appropriateness, for instance, by conducting interviews. It would also allow to discuss the particularities of the specific respondent. This approach, however, is very time consuming (and hence costly) and would again require a lot of effort, both from the hospitals and the research team.

4.4 Conclusion

In this chapter we surveyed the hospitals in Flanders on their current practice on operating theater planning and scheduling. An electronic questionnaire was sent to 95 hospitals in which surgeries are performed, which eventually resulted in a well-balanced response set of 52 hospitals (55%). An increased utilization of the operating theater and reduction in the amount of operating room overtime were identified as the main objectives, which hospitals try to realize by applying a modified block scheduling approach. The tardiness of the patient, emergency arrivals and surgical complications seem to constitute the main causes of disrupted surgery schedules, which hospitals try to fix in a reactive way. Despite the proliferation of computerized planning and scheduling procedures proposed by the scientific community, the implementation rate of satisfying technological planning or evaluation systems still seems to be low. In order to increase the operating room efficiency and to create awareness of operations management capabilities, a closer cooperation between the academic institutions and the practitioners should be encouraged.

Chapter 5

Algorithms for sequencing surgical cases in a day-care environment

The previous chapters of this dissertation outlined the broad domain of operating room planning and scheduling issues. From this chapter on, we narrow the scope to one particular scheduling problem that originated from the daily practice at the surgical day-care center of the UZ Leuven Campus Gasthuisberg. The question we address is how to determine the sequence of surgeries in each operating room of the day-care center so that an overall qualitative schedule is obtained without violating a specific set of constraints.

In Section 5.1 we introduce the day-care center, describe its current practice and as such provide a motivation for the study. After setting the general scope, Section 5.2 provides a detailed listing of the objectives and constraints that constitute the combinatorial optimization problem, which we will prove to be NP-hard in Section 5.3 using a proof by restriction. The next two sections are devoted to the development of solution procedures. In Section 5.4 we develop a dedicated branch-and-bound procedure, whereas Section 5.5 describes various mixed integer linear programming approaches. The performance of the algorithms and procedures is consecutively evaluated in Section 5.6 using a computational experiment in which the test instances are generated based on real and expert data. Some further extensions of the problem setting are highlighted in Section 5.7. Section 5.8 concludes this elaborate chapter and summarizes the most important findings.

5.1 Introduction

The surgical day-care center of the UZ Leuven Campus Gasthuisberg (Belgium), which already has been the subject of research in a case study of Beliën et al. [16], yearly accounts for about 15000 hours of total net operating time and for 13000 ambulatory surgeries, i.e. surgeries of patients who are admitted and discharged on the same working day. Since this day-care center has the ability to operate independently from the inpatient sections of the hospital, we refer to it as a freestanding unit or facility.

Figure 5.1 depicts a floor map of the day-care center. In general, patients follow a common trajectory through the center on their day of surgery, as indicated by the arrows. The hospital requests patients to arrive at the center approximately one hour before the planned surgery start. After a short registration at the reception, they take place in the waiting room. Since this waiting room features e.g. comfortable seats, internet access or a playground for children, it does not resemble a traditional hospital waiting room and hence creates a soothing atmosphere. After a certain waiting time, a nurse accompanies the patient to the locker rooms in which the patient can switch clothes. With the use of a locker system, the hospital shows the patient that their visit is temporarily, which again should reduce anxiety. Next, the patient is transferred to the preparation boxes in which pre-surgical interventions are performed, such as the placement of a catheter or additional shaving. After the preparation, the patient is moved into the specific operating room in order to undergo the surgery. As indicated in Figure 5.1, the day-care center comprises 8 operating rooms. After surgery, the patient is admitted to PACU 1 where he or she stays during the critical awakening phase. When the patient is conscious and the awakening process tends to be normal, a transfer to PACU 2 (beds) or PACU 3 (chairs) takes place. The patient stays there until the surgeon gives permission to leave the hospital, after visiting the reception desk once more.

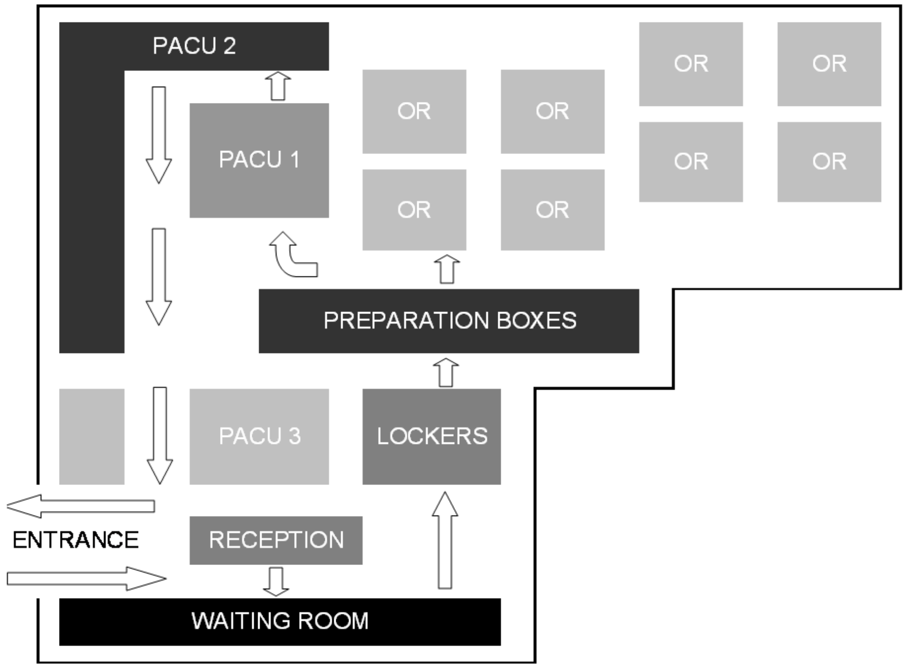

Figure 5.1: Floor map of the freestanding surgical day-care center of UZ Leuven Campus Gasthuisberg

Although the flow of Figure 5.1 applies to the major share of patients, deviations may occur. Sporadically, an inpatient surgery is performed at the day-care center. After surgery, however, these patients are transferred to other PACU areas in the hospital which eliminates their stay in PACU 2 or PACU 3. Other deviations are, for instance, triggered by the type of anesthesia that is applied to the patient. Surgeries that are performed under local or regional anesthesia do not require a visit to PACU 1 so that patients are immediately transferred to PACU 2 or PACU 3 (see Chapter 6). It should be noted that the arrival of a patient in the recovery area depends on the surgery schedule. In other words, a change in the sequence (starting time) of surgeries triggers a change in the resulting workload per period in the recovery area. Consider Figure 5.2 to illustrate this remark. The surgery of the patient starts on period 2 and ends on period 5. After surgery, the patient is immediately transferred to PACU 1 where he or she recovers for 3 periods. After the recovery in phase 1, the patient finalizes

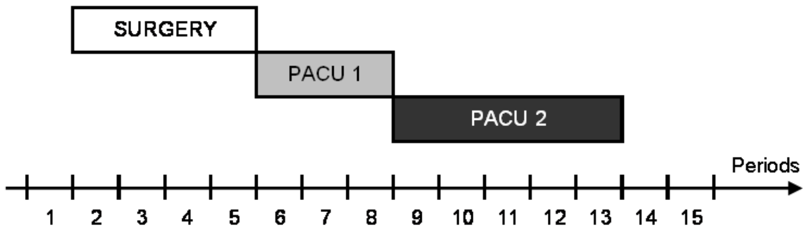

Figure 5.2: Illustrating the dependency of the recovery start times on the surgery start time

his or her recovery in phase 2 for another 5 periods. Changing the surgery starting time to period 4 implies that the patient would arrive in PACU 1 on period 8 and in PACU 2 on period 11. Note that when we would eliminate in Figure 5.1 the stay in PACU 1, this would imply that the patient is immediately moved to PACU 2 (on period 6) after finishing the surgery. Since the duration of the surgeries and the stays in recovery largely vary among the various interventions, sequencing surgeries embeds potential to reduce workload peaks in recovery (see Section 5.2.1). Since patients in the recovery area may arrive from each of the 8 operating rooms, it should be clear that these operating rooms cannot be sequenced independently. This observation does not only stems from the use of downstream resources, but also from resources needed during surgery execution, such as medical equipment (see Section 5.2.2).

The current procedure for scheduling surgical cases at the day-care center is based on two steps, namely an assignment step and a sequencing step. In a first step, the assignment phase, patients are assigned to days and surgery slots. The assignment results from a negotiation between patient and surgeon and is based on their preferences and the amount of free operating slot capacity. A slot represents a large block of operating room time that is reserved for a specific medical discipline or surgeon. Remark that the patient is at this time unaware of the timing of the surgery, i.e. when they have to enter the day-care center at the particular agreed-upon day. This is a decision that has to be made in the second (sequencing) step. The sequencing of the surgeries within each slot is performed exactly one day in advance of the surgery execution. This implies that the entire population of patients for that particular day, varying from 45 to 70 patients, is known to the head nurse of the day-care center's operating theater. Although the surgeons may specify a preferred sequence, the head nurse may introduce changes to these sequences in order to resolve conflicts that may arise between slots. When an appropriate sequence is determined, patients are informed about their expected time of arrival. This contact, close to the day of surgery, has a significant beneficial effect on the degree of no-shows [170, 203]. Remark that the overall quality of the final surgery schedule strongly depends on the assigned population. If this population restricts the pool of feasible schedules too much due to, e.g., tight medical equipment or bed constraints, sequencing will only marginally improve the schedule quality. In this research, however, we assume that the population of patients for a specific surgery day is known in advance so that we restrict the focus to the sequencing step, i.e. determining the starting times of the surgeries within each operating room slot.

The literature provides some studies in which similar operating room planning and scheduling problems are solved using a two-step procedure. The precise delineation of the two steps, however, differs amongst the researchers. Jebali et al. [144] distinguish between the assignment of surgeries to the operating rooms and the sequencing of these surgeries within each operating room. In the assignment step ($NS \mid pat; date, room; int(ICU) \mid det \mid multi; util(under - over), wait$), they try to minimize operating room overtime, undertime and patient waiting time (between surgery and hospitalization day), whereas the objective in the sequencing step is limited to overtime minimization. They examine the sequencing step both with ($NS \mid pat; date, time, room; int(PACU) \mid det \mid single; util(over)$) and without ($NS \mid pat; time; int(PACU) \mid det \mid single; util(over)$) reconsidering the assignments made in the first step. The objective functions are formulated in terms of costs and are optimized using a mixed integer linear programming approach. A similar two-step procedure is favored by Guinet and Chaabane [120], though their focus lies primarily in the assignment phase ($NS \mid pat; date, room; iso \mid det \mid multi; util(over), wait$). Using a primal-dual heuristic, they try to optimize the patient waiting time and the operating theater overload. Sier et al. [252] describe the sequencing step as a mixed integer nonlinear programming formulation and develop a simulated annealing heuristic in order to optimize their multi-objective function (NS | $pat; time; iso$ | det | $multi; util(over), pref, other$). The sequencing step was also the subject of research by Hsu et al. [136]. They introduced a tabu search-based heuristic in order to minimize the number of nurses in the single PACU and the completion time of the last patient in that unit (out | $pat; time; int(PACU)$ | det | $multi; level, C_{max}$). Similarly to the research of this chapter, their model is developed for an ambulatory surgical center. A different two-stage approach can be identified in Marcon et al. [184]. In order to master the risk of no realization of surgeries, they make a distinction between a static and a dynamic phase. During the static phase, a multiple knapsack problem is solved in order to get to a fixed schedule. The risk of no realization is captured either by leveling the workload of the operating rooms (NS | $pat; room; iso$ | $stoch(dur)$ | $single; level$) or by avoiding operating room overtime (NS | $pat; room; iso$ | $stoch(dur)$ | $single; util(over)$). They state, however, that the execution of this schedule during the surgery day will be influenced by unforeseen events. The monitoring and rescheduling due to these events is done in the dynamic phase. Both integer programming and simulation are used to evaluate their procedure. We refer to the literature review of Chapter 2, and more specifically to the set of tables, for further information on these references.

As mentioned, the current sequencing approach at the day-care center results from negotiations between the surgeons and the head nurse of the operating theater. While surgeons in general limit their scope to their individual preferences, the head nurse focuses on the quality of the schedule as a whole. Although this methodology is common practice since the opening of the day-care center in 2002, it has some major disadvantages. Changes made by the head nurse, for example, are often perceived as unfair. Moreover, these changes are induced by rules of thumb that do not cover complex interactions, such as the demand for recovery bed spaces, and hence result in inferior or even infeasible surgery schedules (see Chapter 6). The process is furthermore very time-consuming due to the lack of an efficient decision support system. The algorithmic solutions of Section 5.4 and Section 5.5 will assist the head nurse in generating fair, i.e. computerized and thus less subjective, and improved surgery schedules that surpass the level of detail of the hand-made schedules by far.

5.2 Problem statement

In this section, we introduce the specific set of objectives and constraints that constitute the operating room sequencing problem of the UZ Leuven Campus Gasthuisberg. Using the classification scheme that is developed in Chapter 3, the problem is described as $out \mid pat; time; int(PACU) \mid det \mid multi; level, util(over), pref$. This means that we deal with a deterministic scheduling problem in which surgery starting times have to be assigned to outpatients in such a way that a multi-objective function is optimized. This function incorporates leveling aspects, overutilization of resources and stakeholder preferences. The impact of changing the starting times is furthermore explicitly linked to the PACU. The next subsections address the problem statement in more detail. A mathematical formulation of the objectives and the constraints is provided in Section 5.5.1. Note that the problem statement does not cover the processes related to the waiting room, locker rooms, preparation boxes or PACU 3, as these facilities currently do not represent any operational bottleneck.

5.2.1 Objectives

The surgical case sequencing problem at hand (SCSP) maximally comprises 6 objectives ($|J| \leq 6$) that have to be optimized simultaneously. As such, we need to combine them into a multi-objective function that well balances their importance.

5.2.1.1 Description of the objectives

A first objective concerns the surgery scheduling of children (age $\leq$ 5 years). For medical reasons, patients need to be sober when the surgery is performed. Contrary to adults, children cannot easily cope with this obligation

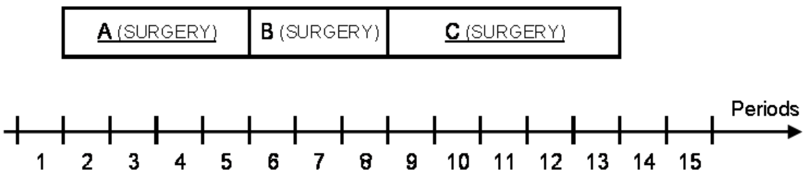

Figure 5.3: Surgery sequence to clarify the calculation of α_1 (children as early as possible)

and the lack of food can cause parents, surgeons, nurses or patients a lot of annoyance. Therefore, it is desirable to schedule these surgeries as early as possible. In particular, we want to minimize the sum of the starting times of surgeries performed on children. This objective is represented by the variable α_1 and is expressed in periods. Figure 5.3 clarifies the resulting value for α_1 based on the surgery sequence. When we assume that the underlined surgeries represent children, the value for α_1 is determined as $\alpha_1 = 2 + 9 = 11$. Note that a switch of surgery B and surgery C would decrease the objective value to $\alpha_1 = 2+6 = 8$ and hence result in a superior sequence (at least for this objective).

The second objective is very similar to the first one, though this time we are concerned about prioritized patients. This category represents, for instance, patients who already had a canceled surgery once or surgeries that the surgeon preferably performs in the beginning of the slot. Similarly to the children, we want the surgeries of the prioritized patients to be scheduled as early as possible, i.e. we want to minimize the sum of their starting times. We distinguish between the children and the prioritized patients as the weight that is assigned to the objectives can be different (see Section 5.2.1.2). The value for this objective is represented by the variable α_2 and is expressed in periods.

Third, we want to incorporate the travel distance between the patient's residence and the day-care center while constructing the surgery schedule. Although the day-care center of the UZ Leuven Campus Gasthuisberg is centrally positioned in Belgium, it is possible that patients have to travel

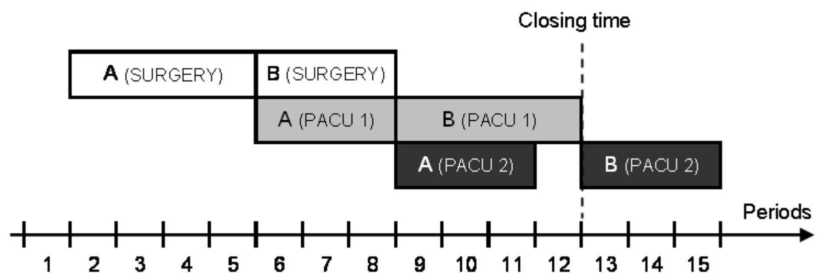

Figure 5.4: Surgery sequence to clarify the calculation of α_4 (minimization of recovery overtime)

over 150 kilometers. The aim is to schedule these patients from a certain reference period (e.g. 11 a.m.) on. Penalty costs are incurred for patients whose surgery starts before the reference period. This cost is represented by the variable α_3 and equals the number of patients with a surgery starting time that precedes the reference period. The relevance of this objective is twofold. On the one hand, there is an increase in patient satisfaction if the patient's effort to get in time to the day-care center is not too large. On the other hand, providing more time to enter the hospital reduces the probability to arrive late due to traffic uncertainty.

Fourth, we want to minimize the stay in recovery after the closure of the day-care center at 7 p.m., as this results in unplanned (and hence costly) hospitalizations or overtime for the nursing personnel. In particular, we minimize the number of periods in which recovery care has to be provided after closing time ($=\alpha_4$). Figure 5.4 clarifies the calculation of this variable. In the example, the day-care center closes after period 12. However, the current surgery sequence results in a stay of patient B in PACU 2 from period 13 to period 15, so that $\alpha_4 = 3$. When the closing time is advanced by one period, the recovery overtime would increase with one more period, namely a fraction of the stay of patient B in PACU 1 ($\alpha_4 = 1 + 3 = 4$).

Finally, we are interested in minimizing the peak number of bed spaces used in PACU 1 ($=\alpha_5$) and PACU 2 ($=\alpha_6$) in order to level the bed occupancy and hence level the workload of the nursing personnel. In Section 5.1 we already pointed at the different degree of monitoring between both recovery phases. Note that the leveling furthermore protects the flow of patients from the operating room to the PACU in case of schedule deviations as spare recovery capacity is more likely to be available. This should reduce the probability of *bed blocking*, in which the patients stays in the operating room until a recovery bed is idle. It should be clear that bed blocking is very expensive and hence has to be avoided. In practice, solutions to bed blocking are found in a quick transfer of patients from PACU 1 to PACU 2 when capacity is lacking in PACU 1, although this clearly decreases the degree of patient satisfaction and service quality (see Section 6.3.4). When we return to the example sequence of Figure 5.4, it should be clear that the peak use of recovery bed spaces in PACU 1 equals the peak of PACU 2, namely one single bed space ($\alpha_5 = \alpha_6 = 1$).

5.2.1.2 Towards a multi-objective function

Intuitively, it seems necessary to take multiple objectives into account. When we would optimize the surgery schedule for one single objective, it is very likely that the schedule performs poorly with regard to some other objective. Question is, however, how we should combine the objectives into a well-balanced multi-objective function. One approach is to sum the values for each objective, i.e. $\sum_{j \in J} \alpha_j$. However, since the objectives are expressed in various units with a different granularity, this formula is not adequate. Moreover, it does not incorporate a notification of the (varying) importance that the scheduler assigns to each objective. One solution exists in the introduction of a weight w_j for each objective j, determined by the human scheduler, so that the multi-objective function is transformed to $\sum_{j \in J} w_j \alpha_j$. The weights now incorporate both a trade-off between the units and an indication of the objective's importance. Setting these type of weights manually, however, is a very subjective decision, even for an experienced planner, and is difficult to argument. What is the trade-off between a period and a bed space? As such, the scheduling process may result in schedules that are not very favorable for the decision maker due to the mismanagement of the weights.

We suggest to combine the objectives as represented in Expression (5.1). Recall from Section 5.2.1.1 that α_1 (α_2) equals the sum of the surgery starting times of children (prioritized patients), α_3 equals the number of travel patients that is scheduled before the reference period, α_4 equals the total amount of recovery overtime (expressed in periods) and α_5 (α_6) equals the peak number of bed spaces used in PACU 1 (PACU 2). It should be clear that the expression has to be minimized in order to find an optimized surgery schedule.

$$\sum_{j \in J} w_j \cdot \left(\frac{\alpha_j - bestvalue_j}{worstvalue_j - bestvalue_j} \right) \tag{5.1}$$

Expression (5.1) proposes a type of normalized objective function that originates from the field of multiple criteria decision making (e.g. [209]). Since the patient population is known, we should be able to calculate for each single objective j, i.e. leaving all other objectives out of consideration, its best value ($bestvalue_j$) and its worst value ($worstvalue_j$). In other words, each feasible schedule features values for α_j that satisfy $bestvalue_j \leq \alpha_j \leq worstvalue_j$, which is easy to interpret. These extreme values are consecutively used as indicated in Expression 5.1 to generate a relative measure of quality, i.e. the transformation discards the different units of the objectives. One could argue why we do not divide α_j by $bestvalue_j$ and optimize this kind of transformation as it would be a relative measure too. However, since the best value for an objective j possibly equals 0, this would result in a division by 0. One could argue again that the denominator of Expression 5.1 also equals 0 when $bestvalue_j$ equals $worstvalue_j$. Then, however, we do not take the optimization of objective j into account as it implies that the value of objective j is optimal for every feasible schedule that is obtained. This also implies that the set of objectives $|J|$ for a particular surgery day not always equals 6 ($0 \leq |J| \leq 6$). The number of objectives that are eventually incorporated in the problem setting depends on the constitution of the patient population of the specific day.

The stabilizing transformation or normalization ensures that all objectives $j \in J$ will be gradually optimized to the same extent and that they will somehow be comparable to each other. It is unlikely, however, that the objectives are of equal importance to the human planner. Thus, we also incorporate a differentiator by assigning a weight w_j to objective j. Note that the weights now only indicate the preferences of the scheduler. When the sum of the weights equals 1, the multiple objective function has a value that is in the range $[0, 1]$. A value equal to 1 denotes that each α_j is equal to its $worstvalue_j$, whereas a function value of 0 indicates that $\forall j \in J : \alpha_j = bestvalue_j$. We refer to Section 5.6.2 for a discussion on the calculation of the extreme values.

5.2.2 Constraints

Next to the various objectives, a substantial set of constraints has to be introduced to describe the problem statement. Surgery schedules are infeasible whenever at least one of the constraints below is violated (hard constraints).

First of all, each surgeon is restricted to start and end his or her surgeries during the time and in the operating room that is assigned by the master surgery schedule (see Chapter 2). Each surgery has a slot identification and all surgeries have to be scheduled in a slot that matches the surgery's slot ID. Let M_s^{lb} denote the beginning period of slot s and M_s^{ub} denote its ending period. For each surgery that has to be scheduled in slot s, it holds that $M_s^{lb} \leq$ surgery starting time $\leq M_s^{ub}$.

When building the surgery schedule, it is essential that each surgeon's total population of patients is planned, i.e. all patients have to receive a surgery starting time on the day of surgery. Since the surgeries are not allowed to overlap in the same operating room, a surgery cannot start when the operating room is occupied by any other surgery.

On entering the day-care center, patients possibly still have an incomplete file. This means that these patients still have to do some pre-surgical tests (e.g. X-ray) on the day of surgery. In order to do so, such patients are expected to arrive early in the hospital, although their surgery is only scheduled later on the day. As such, a sufficient amount of time is created for the patient to do the tests and obtain the results. Conceptually, we can add this constraint through the introduction of a reference period for additional tests, set by the scheduler. In particular, we require that surgeries of patients with incomplete files start on or after the reference period.

Both recovery areas (PACU 1 and PACU 2) are characterized by a limited availability so that the peak demand for recovery bed spaces in each PACU (α_5 and α_6) cannot exceed the total number of bed spaces available.

Since medical equipment is needed during surgery and the availability is again limited, potential bottleneck instruments should also be incorporated in the problem setting. For each type of medical instrument (e.g. lasers, towers or drills) and for each period we require that the number of instruments used in that period does not exceed its total capacity. Note that the availability of the instruments does not solely depend on the simultaneous use over the set of operating rooms while surgeries are performed. After surgery, instruments possibly need to be sterilized for several periods (about 240 minutes) and hence cannot be used for subsequent surgeries.

Finally, we also have to deal with the occurrence of MRSA (Methicillin-Resistant Staphylococcus Aureus). The spread of this infection, which is very hard to be treated due to its resistance to a large group of antibiotics, is especially troublesome in hospitals due to the increased amount of weaker people. Therefore, special sanitary procedures are in place to avoid the transfer of MRSA from patient to patient. In particular, after surgery of an infected patient, the operating room needs additional cleaning. This takes about 30 minutes, as the operating room is scrubbed with a special liquid that has to dry. This cleaning, however, is not obligatory when the next patient is also infected by MRSA. No additional cleaning is required when an infected patient is the last one to be treated in an operating room, as the entire operating room is thoroughly cleaned at closing time. However, when an infected patient is scheduled in a slot that is followed by a slot of a different surgeon, the cleaning is again obligatory and it should be entirely performed in the slot of the infected patient.

5.3 Complexity analysis

In this section we will prove that the optimization of the SCSP is computationally hard, i.e. NP-hard, by showing that it contains a problem, for which the optimization is already shown to be NP-hard, as a special case. This technique is referred to as a proof by restriction [105]. In particular, we will specify restrictions so that the restricted SCSP, which we will refer to as R-SCSP, is identical to the *resource investment problem* (RIP). The RIP is situated in the domain of the *resource-constrained project scheduling problems* (RCPSP) and the optimization is shown in Neumann, Schwindt and Zimmerman [199] to be NP-hard. We may summarize the characteristics of the RIP as follows:

- PROBLEM: Resource investment problem (RIP)
- INSTANCE: A set of precedence-related activities that constitute a project. The project has to be finished before the project deadline. Each activity consumes resources during each period of its execution according to a particular resource consumption pattern. Each resource has a limited availability at each time instance p.
- GOAL: $MIN\ \sum_o cost_o \cdot max_p\ consumption_{op}$: minimize the costs that are associated with the peak use of each resource during the course of a project by determining the activity starting times. In the expression, $cost_o$ denotes the procurement cost per unit of resource o and $consumption_{op}$ denotes the number of units of resource o that are needed in period p.

Theorem 1. *Problem SCSP is NP-hard.*

Proof of Theorem 1. In the R-SCSP, we only take objective 5 and 6 into account, i.e. minimizing the peak number of bed spaces used in PACU 1 and

PACU 2. We furthermore restrict the focus to a single surgery slot s and do not incorporate constraints concerning the medical equipment, incomplete pre-surgical tests or MRSA.

We cannot straightforwardly identify the RIP in the R-SCSP as there is a problem with the activity representation. We cannot define an activity for the RIP to be equal to an entire surgical process of a patient since this process is actually a sequence of three distinct activities. First, there is the surgery itself, which takes place in the operating room. Second, a recovery process is initiated in PACU 1. Finally, the patient is transferred for a second recovery process to PACU 2. The last two activities, though, consume resources when the surgery itself is already finished. This feature is not typical for the RIP and some modifications should hence be introduced. Instead of scheduling one activity that contains 3 processes (surgery, PACU 1 and PACU 2), we will schedule 3 precedence related (fictive) activities, namely n', n'' and n''' in such a way that each activity now represents only one process. This substitution is depicted in Figure 5.5. In this figure, an activity-on-the-node representation is introduced. The duration of the activity is indicated above the node, whereas the resource consumption is indicated below using a vector. Only three resource types are represented in the R-SCSP, i.e. the operating room ($o = 1$), beds of PACU 1 ($o = 2$) and beds of PACU 2 ($o = 3$). The consumption of these resources by each activity is indicated in the respective entries of the vector: $\overrightarrow{res}_{n''} = (0, 1, 0)$, for instance, denotes that only one resource is seized, namely a bed in PACU 1, when activity n'' is performed. The minimal and maximal zero time lags ($FS_{MIN} = 0$ and $FS_{MAX} = 0$) between the activities $n' - n''$ and $n'' - n'''$ in Figure 5.5 indicate that no time is allowed between the completion of the former and the start of the latter activity.

The equivalence between the RIP and the R-SCSP should now become transparent. We still have to introduce some modifications in order to complete the activity-on-the-node representation of the RIP. We have to define, for instance, a dummy start and a dummy end activity and add a $FS_{MIN} = 0$ precedence relation both between the dummy start activity and each first

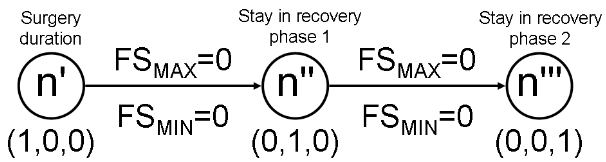

Figure 5.5: Representing a surgical process as a sequence of its constituent activities.

activity n' of a substituting sequence and between the last activity n''' of a sequence and the dummy end activity. Moreover, a $FF_{MAX} = M_s^{ub} - M_s^{lb} + 1$ precedence relation needs to be specified between the dummy start node and each activity n' that represents a surgery in order to capture the project deadline. Recall from Section 5.2.2 that M_s^{lb} represents the starting period of slot s and that M_s^{ub} equals the ending period of slot s. Note that, based on the precedence relation, the workload that has to be sequenced in a slot is equal to the capacity of the slot. This, however, does not imply that idle time cannot be incorporated as this is easily done by introducing a surgery that does not consume any resource, except for the operating room. The dummy start activity is completed at time $p = M_s^{lb}$. Since the surgical act inevitably needs an operating room to be performed in and the capacity of this resource is limited to 1 in the R-SCSP, we do not take the leveling of this resource into account (best value equals worst value in this case). Both the peak number of bed spaces in PACU 1 ($max_p\ consumption_{2p} = \alpha_5$) and PACU 2 ($max_p\ consumption_{3p} = \alpha_6$), on the contrary, have to be minimized. The procurement cost related to these resources is equal to $cost_2 = w_5/(worstvalue_5 - bestvalue_5)$ for the use of one bed space in PACU 1 and equal to $cost_3 = w_6/(worstvalue_6 - bestvalue_6)$ for the use of one bed space in PACU 2.

$\Rightarrow$ Assume that we have a solution to the RIP, i.e. we know for each patient n the start times $v_{n'}$, $v_{n''}$ and $v_{n'''}$ of the constituent activities, then we can construct a solution for the R-SCSP as follows: $\forall n$ in the patient population: the surgery of patient n in slot s starts on period $v_{n'}$.
$\Leftarrow$ Given a solution to the R-SCSP, we can construct a solution for the RIP as follows: $\forall n$ in the patient population, we know that the surgery starts in

slot s on period $v_n \Rightarrow\ v_{n'} = v_n,\ v_{n''} = v_n+$ surgery duration of patient n and $v_{n'''} = v_{n'}+$ stay of patient n in PACU 1. $\Box$

5.4 Solution approach: Branch-and-bound

In Section 5.3 we mentioned the relation between the SCSP and the RCPSP. Since we know that the literature provides some powerful branch-and-bound procedures to solve the RCPSP (e.g. [51, 149]), we may wonder whether implicit enumeration through a dedicated branch-and-bound algorithm would also be beneficial to solve the SCSP. The next three subsections respectively introduce a basic, nested and iterated branch-and-bound procedure. We refer to Section 5.6 for information on the computational performance of the presented algorithms. An overview of some frequently used symbols to clarify and formulate the problem setting, both with respect to the branch-and-bound procedures and the MILP approaches, is given in Table 5.1.

5.4.1 Basic branch-and-bound

We structure the discussion of the basic branch-and-bound algorithm, which is an exact procedure, according to Agin [3]. In his generalized description of branch-and-bound algorithms, a distinction is made between the branching characteristic and the bounding characteristic. The branching characteristic guarantees that the algorithm will eventually obtain an optimal solution, whereas the bounding characteristic enables the algorithm to end up with an optimal solution without complete or explicit enumeration of all solutions.

5.4.1.1 Branching characteristic

Each node of the branch-and-bound tree represents a subset of the set of solutions of the parent node. We have to decide, however, how we will partition the subset of the parent node. This partitioning is often referred to as the *branching scheme*. In particular, two decisions need to be made. First, we have to identify the slot in which we want to schedule the next surgery. The choice of the slots actually determines the shape of the partial surgery schedule during the optimization process. We could, for instance, decide to entirely fill up the first slot with surgeries before we switch to a second

Table 5.1: Overview of frequently used symbols in the MILP formulations

Indices	
i	surgery type
p	period
s	slot
t	column
e	instrument type
j	objective
Sets	
S	set of slots
T_s	set of feasible columns for slot s
J	set of objectives: $\forall j \in J : worstvalue_j \neq bestvalue_j$
E	set of instrument types
P	set of five-minute periods
N_{is}	set of patients with a surgery of type i to be performed in slot s
Variables	
x_{ips}	binary decision variable that equals 1 if surgery of type i starts on period p in slot s, 0 otherwise
z_{st}	binary decision variable that equals 1 if column t is chosen for slot s, 0 otherwise
α_1	sum of the surgery starting times of children (in periods)
α_2	sum of the surgery starting times of prioritized patients (in periods)
α_3	number of travel patients scheduled before reference period
α_4	amount of recovery overtime (in periods)
α_5	peak number of bed spaces used in PACU 1
α_6	peak number of bed spaces used in PACU 2
Parameters	
k_i	length of surgery of type i (in periods)
l_i	length of recovery phase 1 for surgery type i (in periods)
m_i	length of recovery phase 2 for surgery type i (in periods)
M_s^{lb}	first period of slot s
M_s^{ub}	final period of slot s
$ster_e$	periods needed to sterilize instrument of type e
$PACU1cap$	number of bed spaces available in PACU 1
$PACU2cap$	number of bed spaces available in PACU 2
cap_e	number of instruments of type e available
a_{pst}^e	units of instrument e occupied in period p when column t is chosen for slot s
Θ_i^{child}	equals 1 if surgery of type i implies that the patient is a child, 0 otherwise

slot. Alternatively, we could continuously alternate between the slots or choose slots in such a way that the (intermediate) workload in each slot is somehow leveled. Obviously, combinations of these branching schemes can be made. The scheme that incorporates alternating slots is applied during the computational testing of the algorithm (see Section 5.6) as we hope to detect resource conflicts near the top of the tree. Second, we have to decide which surgery type has to be scheduled next. Obviously, this should be a surgery type that is allowed to be scheduled in the chosen slot. What type of surgery exactly will be chosen depends on a pre-sequenced list of surgery types of which the order is determined at the root node. We prefer to add surgery types to the schedule instead of patients for it is not uncommon that a surgeon has multiple patients who have to undergo the same surgery type. Introducing surgery types hence tackles symmetry in the problem setting. Remark that the above branching process results in a non-binary tree.

Based on the selection of the node to branch from next, two general *branching strategies* can be defined, namely a depth-first or backtracking strategy and a best-first or skiptracking strategy. Since surgery schedules have to be generated in limited time and the construction of at least one feasible surgery schedule is crucial for the practical implementation, a depth-first approach seems to be advantageous. Moreover, this strategy tends to be more flexible in handling computer memory restrictions.

5.4.1.2 Bounding characteristic

Several bounding techniques will be applied in order to limit the tree search. Next to the introduction of a lower bound calculation and a fathoming rule, we will also check the viability of a dominance rule.

It is not straightforward to calculate a tight lower bound due to the multiple objectives. In fact, we will calculate a lower bound for each objective and merge them into one value. For each objective $j \in J$ we will calculate the corresponding α_j of the partial schedule. Next, we will try to augment α_j for $j \in J : j \leq 4$ by analyzing the set of surgeries that still have to be scheduled. In particular, we will try to add the remaining surgeries to the schedule in such a way that the corresponding α_j is kept as small as possible. This will be done for each objective individually and with the relaxation of the instrument, MRSA and bed constraints in order to speed up computation time. Since augmenting α_j for $j \in J : j \geq 5$ can still be computationally expensive and the lower bound has to be frequently calculated, we do not consider the augmenting step for these objectives. When the value of α_j is smaller than $bestvalue_j$ (due to the relaxations), we set $\alpha_j = bestvalue_j$.

A second bounding procedure is captured in a fathoming rule. When an infected patient or an idle period is scheduled, we examine whether a feasible schedule can still be obtained. This rule implies that we determine the minimal number of idle periods needed to generate a feasible schedule. If this number is larger than the remaining number of idle periods, we fathom the node and consequently backtrack.

Finally, we also thought of a dominance rule in which we tackle symmetry. We focus on the current partial schedule and try to identify for a specific surgeon s two surgeries for which a swap is favorable. Below we will show that the favorability of a swap does not necessarily imply that there is a decrease in the objective function. When we assume that $|J| = 6$ and that a surgery of type i' was just added to the partial surgery schedule with a starting time equal to period p', we want to find a surgery of type i that has a starting time $p : p < p'$. Furthermore, we request that $i \neq i'$ and that the surgery types are the same with respect to their surgery duration, stay in PACU 1, stay in PACU 2 and the use of medical equipment. When two surgeries can be identified that satisfy these conditions, we need to check the feasibility of the swap with respect to the incomplete pre-surgical tests and MRSA when needed. When the swap is free of feasibility conflicts, we may calculate its favorability by summing Expression (5.2) to (5.4). In these expressions, θ_i^{child} equals 1 if the surgery of type i concerns a child (0 otherwise), θ_i^{prior} equals 1 if the surgery of type i concerns a prioritized patient (0 otherwise) and θ_i^{travel} equals 1 if the surgery of type i concerns a travel patient (0 otherwise). $travelref$ stands for the reference period on or after which travel patients are preferably scheduled.

$$\triangle\ objective\ 1 = \frac{w_1 \cdot [(\theta_{i'}^{child} - \theta_{i}^{child}) \cdot (p' - p)]}{worstvalue_1 - bestvalue_1} \tag{5.2}$$

$$\triangle\ objective\ 2\ = \frac{w_2 \cdot [(\theta_{i'}^{prior} - \theta_{i}^{prior}) \cdot (p' - p)]}{worstvalue_2 - bestvalue_2} \tag{5.3}$$

$$\triangle\ objective\ 3 = \begin{cases} 0, \text{ if } (travelref \leq p) \text{ or } (travelref > p') \\ \\ \frac{w_3 \cdot (\theta_{i}^{travel} - \theta_{i'}^{travel})}{(worstvalue_3 - bestvalue_3)}, \text{ otherwise} \end{cases} \tag{5.4}$$

Since both the stay in PACU 1 and the stay in PACU 2 are equal for a surgery of type i or i', a swap has no effect on objective 4, 5 or 6. We can now state the dominance rule in Theorem 2. The proof of this theorem is trivial and is hence omitted.

Theorem 2. *When $\triangle$ objective 1 + $\triangle$ objective 2 + $\triangle$ objective 3 > 0, the current partial schedule is dominated and the algorithm can backtrack until the specific surgery of type i that starts on period p is removed from the schedule. The backtracking property also holds when $\triangle$ objective 1 + $\triangle$ objective 2 + $\triangle$ objective 3 = 0 and $i > i'$ (tie break).*

5.4.1.3 Pseudo-code

The pseudo-code that is depicted in Algorithm 5.1 summarizes and links the major aspects that were discussed in Section 5.4.1.1 and Section 5.4.1.2. Recall that s stands for slot. $list\_of\_types$ represents the ordered list of surgery types that underlies the choice of surgery types that will be added to the partial schedule. $index$ points at the current position in the $list\_of\_types$ array. The boolean *placed* is true when a surgery takes part in the partial schedule. The number of surgeries that already take part in the partial schedule is tracked by the $level$ variable. This variable coincides with the depth of the tree. Note that the branch-and-bound algorithm is programmed in a recursive way.

Algorithm 5.1 Basic branch-and-bound

```
list_of_types ← GET_SEQUENCE();
best_found ← 1;
s ← 1; level ← 0;
RECURSION(s, level + 1);

RECURSION(s, level);
{
index ← 0;
placed ← FALSE;
while (dominated = FALSE and elapsed_time < TILIM and index < I) do
  eligible ← FALSE;
  while (eligible = FALSE and index < I) do
    index ← index + 1;
    get surgery type using list_of_types and index;
    eligible ← CHECK_FEASIBILITY();
  end while
  if (eligible = TRUE) then
    placed ← ADD_SURGERY();
    lower_bound ← CALCULATE_LOWER_BOUND();
    if (lower_bound < best_found) then
      dominated ← DOMINANCE();
      if (dominated = FALSE) then
        if (schedule is complete) then
          best_found ← lower_bound;
          register schedule;
        else
          determine next operating slot s′ to schedule a surgery;
          RECURSION(s′, level + 1);
        end if
      end if
    end if
  end if
  if (placed = TRUE) then
    placed ← REMOVE_SURGERY();
    if (backtracking due to domination is complete) then
      dominated ← FALSE;
    end if
  end if
end while
}
```

5.4.2 Nested branch-and-bound

In the nested branch-and-bound procedure, we adjust the basic enumeration algorithm of Section 5.4.1 on two levels. On the one hand, we introduce a heuristic in order to rapidly improve the surgery schedule. As such, we can focus the computational effort on a more restrictive pool of qualitative schedules. On the other hand, we try to increase the ability of the algorithm to find at least one feasible solution within the time limit. We want to stress that the modifications do not damage the exact nature of the algorithm.

5.4.2.1 Immobility heuristic

Due to the lack of strong bounding characteristics, the basic branch-and-bound procedure does not easily succeed in backtracking to the top of the solution tree (see Section 5.6). This implies that the first scheduled surgeries are somehow immobile and can limit the quality of the schedules that will be explored within the time range. We developed a heuristic that tackles this immobility problem and that is used while generating the tree. Since the heuristic is a branch-and-bound algorithm too, we have a nested algorithm.

The heuristic is applied each time a new best solution is encountered and the corresponding schedule is registered. In particular, we fix the sequence of surgeries in a certain amount of operating room slots, whereas we restart the scheduling process in the other slots. Figure 5.6 should clarify this approach. In this figure, the number of the surgery indicates the order in which they were added to the schedule. Surgeries with a small number hence point at surgeries that are situated near the top of the tree. For ease of reference, we also assume that each operating room represents exactly one slot. We retain the sequence in operating room 2 and 3 and reschedule the surgeries in operating room 1. A second branch-and-bound algorithm, which is structurally comparable to the original procedure, is used to enumerate the feasible sequences within the emptied operating rooms. When the structured searching process of this second algorithm ends, the original branch-and-bound procedure will continue the exploration of the tree from the leaf where the heuristic was evoked.

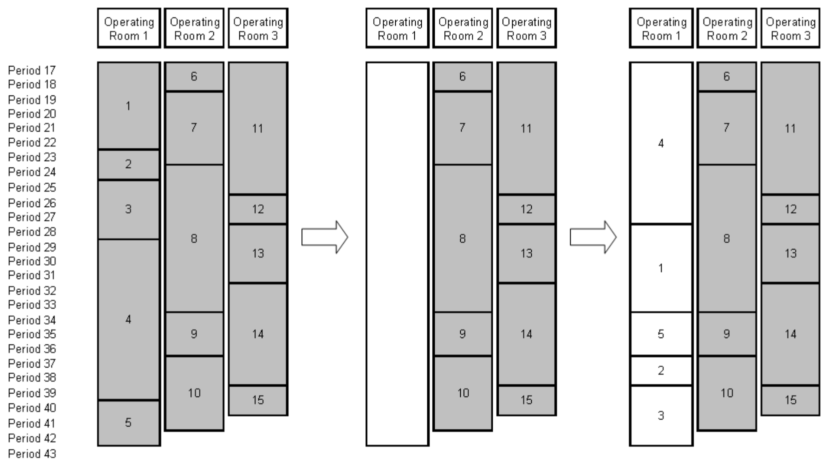

Figure 5.6: Visualizing the heuristic's logic to overcome immobility near the top of the branching tree

The problem in Figure 5.6 is reduced to finding feasible schedules for an SCSP with a single operating room. This reduction in problem size obviously empowers the capabilities of the second branch-and-bound algorithm. Moreover, we can take the capacity of the *fixed* operating rooms, i.e. operating rooms in which we do not alter the surgery sequence, into account to increase the effectiveness of the lower bound calculation. However, when the amount of surgeries that has to be rescheduled is still large, the problem of immobility possibly still occurs in the second branch-and-bound tree. Hence, we continuously truncate the exact procedure, shuffle the list of surgery types that have to be rescheduled and restart the second branch-and-bound algorithm. In the end, various surgeries should be scheduled near the top of the tree and the immobility should disappear.

We still have to decide on the number of operating room slots in which new sequences will be generated. In order to retain the advantages of a limited problem size, we allow for at most 3 slots to be rescheduled. With respect to Figure 5.6, small runs of the second branch-and-bound procedure are executed for each combination of 2 operating rooms (1,2 - 1,3 - 2,3) and for each single operating room. When the surgery schedule comprises more than 3 slots, we also test each combination of 3 operating room slots. Whenever a new best solution is encountered, the entire procedure is repeated.

5.4.2.2 Finding an applicable starting sequence

An obvious approach to reduce the risk of not finding even one feasible surgery schedule within the specified time limits would be to continuously restart the branch-and-bound algorithm with a different sequence in the list of surgery types ($list\_of\_types$ in Algorithm 5.1) and fix the order in that list when the first feasible schedule is encountered. Unfortunately, preliminary results indicate that this approach is not sufficient to guarantee at least one feasible schedule. The main reason is that the recovery capacity constraints for the instances seem to be very tight: there are only few surgery schedules for which these constraints are not violated (see Section 5.6). The modification we introduce is based on loosening the recovery constraints, i.e. we increase the capacity in both PACU 1 and PACU 2, and run the branch-and-bound procedure until an entire schedule is generated. At this point, two possible situations may occur. First, it is possible that the schedule is even feasible with respect to the original or tight recovery capacity constraints. In this case, there is no problem: we should tighten the constraints again and proceed the branch-and-bound algorithm as usual. Second, we could end up with a schedule that is only feasible with respect to the unrealistic constraints. The question now is whether we can easily generate a similar schedule from the one that is obtained that does not violate the original constraints. At this point, the immobility heuristic comes into play once again. The removal of certain surgeries from the schedule will result in a partial schedule that satisfies the tight constraints. Hence we use the second branch-and-bound procedure, i.e. the heuristic, to reschedule the removed surgeries in such a way that the original constraints are not violated. When we are able to find such a tight schedule, we should tighten the constraints again. Otherwise, we should continue the generation of the tree with loosened constraints and repeat the heuristic procedure when the next (possibly infeasible) schedule is encountered. As long as no feasible schedule (w.r.t. the tight constraints) is encountered, the entire algorithm is restarted at certain points in time with a shuffled order in the list of surgery types.

5.4.3 Iterated branch-and-bound

In the previous section, the branch-and-bound algorithm was only restarted when a feasible solution was not yet found. We could argue whether it would be advantageous to restart the algorithm from time to time, even when a feasible solution was already encountered. Restarting the algorithm implies a shift from an exact branch-and-bound procedure towards a heuristic approach: the algorithm now continuously truncates a branch-and-bound procedure and restarts a new one.

The settings of a new iteration may differ from the previous iteration on three levels. First, there might be a difference in the branching scheme (see Section 5.4.1.1). Second, it is possible that the surgery scheduling process starts in a different slot. Finally, there might be, and probably will be, a change in the sequence of the list of surgery types ($list\_of\_types$ in Algorithm 5.1) triggered by a shuffle function. This function incrementally changes the sequence of surgery types that corresponds to the schedule that at that time features the best solution. Applying only minor changes to the provisional best surgery list should stimulate the progression towards a local (but hopefully also global) optimum. In order to get out of local optima, we reset the provisional best solution value after 25000 trials, perform a large number of random swaps on the surgery list and restart the entire procedure. Obviously, we register the overall best solution encountered during the entire algorithmic search.

Truncation of the tree generation algorithm is done by limiting its ability to backtrack. This ability is expressed by the number of surgery removals during an iteration ($REMOVE\_SURGERY()$ in Algorithm 5.1). We randomly distinguish between a small, medium or large number of allowed removals. The choice of this number is renewed each time the number of trials without improvement in the objective function is larger than a limit. This is a self-regulating feature as we do not know whether it is advantageous to have short or extensive tree explorations. The idea is to maintain the backtrack ability of the algorithm as long as new solutions are frequently encountered. Whenever the removal limit is exceeded, the algorithm backtracks to level

0 and a new branch-and-bound iteration is initiated.

The two improvements introduced in the nested branch-and-bound procedure (see Section 5.4.2) are also enabled in this heuristic. Note that the relevance of the immobility heuristic in the iterated branch-and-bound procedure is twofold. On the one hand, it will be called in the search for the first feasible schedule. On the other hand, we will execute the heuristic whenever the best solution value is reset, i.e. after 25000 trials. Note that the schedule that is used in the immobility heuristic does not correspond to the schedule with the overall best solution value but to the one whose solution value is to be reset. This way we encourage the application of the heuristic on diversified schedules.

5.5 Solution approach: MILP

Next to a dedicated branch-and-bound approach, we also examine the capabilities of linear programming (LP) based techniques to solve the SCSP. In Section 5.5.1 we introduce a traditional mixed integer linear programming (MILP) formulation. We refer to this formulation as the basic MILP. The next two sections, namely Section 5.5.2 and Section 5.5.3, introduce two variations on the standard procedure and we refer to them as the preprocessed MILP approach and the iterated MILP approach. Section 5.5.4 concludes the MILP solution approaches and proposes a branch-and-price procedure.

5.5.1 Basic MILP

In order to formulate the basic MILP, we introduce a binary decision variable x_{ips}. This variable equals 1 if a surgery of type i starts on period p in slot s and 0 otherwise. Remark that, similarly to the branch-and-bound procedures, we prefer to formulate the problem in terms of surgery types instead of individual and personalized patients. As such, we hope to reduce the symmetry in the surgery schedules.

In Section 5.2.1.2, we already elaborated on the formulation of the multi-objective function. For ease of reference, we repeat its formulation in Expression 5.5.

$$MIN \sum_{j \in J} w_j \cdot \left(\frac{\alpha_j - bestvalue_j}{worstvalue_j - bestvalue_j} \right) \tag{5.5}$$

Recall that in Expression 5.5, α_1 (α_2) equals the sum of the surgery starting times of children (prioritized patients), α_3 equals the number of travel patients that is scheduled before the reference period, α_4 equals the total amount of recovery overtime (expressed in periods) and α_5 (α_6) equals the peak number of bed spaces used in PACU 1 (PACU 2). In order to integrate these auxiliary variables in the formulation of the basic MILP and relate their values to the surgery starting times, we state the auxiliary variables in terms of the decision variable x_{ips}, as shown in Expression (5.6) to (5.11). In these expressions, Θ_i^{child} (Θ_i^{prior}, Θ_i^{travel}) equals 1 if a surgery of type i implies that the patient is a child (prioritized patient, travel patient). The reference limit, expressed in periods, for travel patients is equal to $travelref$. The amount of overtime, expressed in periods, that results from starting a surgery of type i on period p is captured by $overtime_{ip}$. When k_i, l_i, and m_i respectively denote the duration of a surgery of type i, the stay of a patient in PACU 1 after surgery of type i and the stay of a patient in PACU 2 after surgery of type i and that P^{ub} represents the last period that the surgical day-care center is open, the amount of overtime is calculated as follows: $overtime_{ip} = 0$ if $p + k_i + l_i + m_i - 1 \leq P^{ub}$ and $overtime_{ip} = p + k_i + l_i + m_i - 1 - P^{ub}$ otherwise.

$$\sum_{s} \sum_{i:\Theta_i^{child}=1} \sum_{p} p \cdot x_{ips} = \alpha_1 \tag{5.6}$$

$$\sum_{s} \sum_{i:\Theta_i^{prior}=1} \sum_{p} p \cdot x_{ips} = \alpha_2 \tag{5.7}$$

$$\sum_{s} \sum_{i:\Theta_i^{travel}=1} \sum_{p:p<travelref} x_{ips} = \alpha_3 \tag{5.8}$$

$$\sum_{s} \sum_{i} \sum_{p} overtime_{ip} \cdot x_{ips} = \alpha_4 \tag{5.9}$$

$$\sum_{s} \sum_{i} \sum_{p'=p-k_i-l_i+1}^{p-k_i} x_{ip's} \leq \alpha_5 \qquad \forall p \tag{5.10}$$

$$\sum_{s} \sum_{i} \sum_{p'=p-k_i-l_i-m_i+1}^{p-k_i-l_i} x_{ip's} \leq \alpha_6 \qquad \forall p \tag{5.11}$$

Next to the statement of the multi-objective function and its constituting auxiliary variables, we also have to specify the constraints as shown by Expression (5.12) to (5.20). Recall that M_s^{lb} represents the first period of slot s, whereas M_s^{ub} represents its final period. $|N_{is}|$ denotes the number of surgeries of type i that has to be performed in slot s. Θ_i^{test} equals 1 if the surgery of type i represents a patient with incomplete pre-surgical tests who has to be scheduled before the reference period $testlimit$. Analogously, Θ_i^{MRSA} indicates whether a surgery of type i represents an infected patient (value equal to 1). We already pointed at the (possible) additional cleaning of the operating room after the surgery of an infected patient. The duration of this cleaning is represented by k_{clean} and is expressed in periods. The capacity of medical equipment of type e is denoted by cap_e. The duration of the sterilization of instrument e is captured by $ster_e$ and is expressed in periods. Finally, PACU1cap (PACU2cap) represents the available bed capacity in PACU 1 (PACU 2).

$$\sum_{p=M_s^{lb}}^{M_s^{ub}-k_i+1} x_{ips} = |N_{is}| \qquad \forall i,\ \forall s \tag{5.12}$$

$$\sum_{i} \sum_{p'=p-k_i+1}^{p} x_{ip's} \leq 1 \qquad \forall p,\ \forall s \tag{5.13}$$

$$\sum_{s} \sum_{i:\Theta_i^{test}=1} \sum_{p:p<testlimit} x_{ips} = 0 \tag{5.14}$$

$$\sum_{s}\sum_{i}\sum_{p'=p-k_i-ster_e}^{p} x_{ip's} \leq cap_e \qquad \forall p,\ \forall e \qquad (5.15)$$

$$\alpha_5 \leq PACU1cap \qquad (5.16)$$

$$\alpha_6 \leq PACU2cap \qquad (5.17)$$

$$x_{i'p's} \leq 1 - x_{ips} \qquad \textit{See footnote}\ ^1 \qquad (5.18)$$

$$x_{ips} \in \{0,1\} \qquad \forall i,\ \forall p,\ \forall s \qquad (5.19)$$

$$\alpha_j \geq 0 \qquad \forall j \in J \qquad (5.20)$$

Expression (5.12) states that the entire workload that has to be scheduled in a particular slot is effectively scheduled. Note that we restrict the starting times of surgeries of type i to $M_s^{ub} - k_i + 1$, as a later surgery start would imply that a part of the surgery is performed outside the reserved surgery slot. Expression (5.13) specifies that no overlap is allowed between surgeries. In other words, one surgery has to be finished before another one can be initiated. The obligation that surgeries of patients with incomplete pre-surgical tests have their start to be scheduled before the particular reference period is handled by Expression (5.14). Expression (5.15) states that the number of instruments in use (recall that this includes both the utilization during surgery and the sterilization of the instrument afterwards) cannot exceed the available capacity. Expressions (5.16) and (5.17) respectively restrict the peak demand for recovery bed spaces in PACU 1 and PACU 2 to be smaller than the bed capacity in the units. Expression (5.18) deals with the occurrence of infections as described in Section 5.2.2. Expression (5.19) restricts the decision variables x_{ips} to be binary, whereas Expression (5.20) finally restricts the auxiliary variables to be non-negative.

5.5.2 Preprocessed MILP

The basic MILP approach can easily be enhanced on three levels: next to the modification of some CPLEX-based parameters (Section 5.5.2.1), we may also exploit the structure that stems from infected patients (Section

[1] $\forall p,\ \forall s,\ \forall i : \Theta_i^{MRSA} = 1,\ \forall p' : p \leq p' \leq p + k_i - 1 + k_{clean},\ \forall i' : \Theta_{i'}^{MRSA} = 0$

5.5.2.2) and explicitly fix the values of variables by solving multiple knapsack problems (Section 5.5.2.3). On average about 23% of the decision variables can be fixed to 0 during this preprocessing stage.

5.5.2.1 Parameter tuning

A first improvement involves probing and is readily available in the ILOG CPLEX 10.2 optimization library. Probing is a technique that looks at the logical implications of fixing each binary variable to 0 or 1. It is performed after preprocessing and before the solution of the root relaxation [138]. Applying probing, however, can be time consuming since the probing time is somehow proportional to the difficulty of the instance. This implies that we cannot guarantee that the decrease in solution time outperforms the time needed in the probing phase. Test runs with this single enhancement, however, indicate that probing is worthwhile for the SCSP. Second, we shift the emphasis of the MILP solver towards feasibility. Since less computational effort is spent in the proof of optimality, this feature should reduce the number of instances for which no solution can be obtained within the time limits (see Section 5.6).

5.5.2.2 Exploiting MRSA properties

The presence of infected patients may simplify the scheduling process of surgeries in two ways. On the one hand, there is a possibility to merge idle periods into one large cleaning block with a duration of k_{clean}. This implies that the number of surgeries to be scheduled is reduced (indeed, idle periods, $idle$, are actually surgeries without any resource consumption except for the operating room with a duration equal to $k_{idle} = 1$) and that a reduction in the number of variables is acquired. This reasoning applies when a slot s, which includes the surgery of MRSA patients, has in the same operating room a successor slot s': $M^{lb}_{s'} - M^{ub}_{s} = 1$. Recall that no additional cleaning has to be preserved when the particular slot with the MRSA patients is the last slot in the operating room or when $M^{lb}_{s'} - M^{ub}_{s} \geq k_{clean}$. When $1 < M^{lb}_{s'} - M^{ub}_{s} < k_{clean}$, idle periods are allowed to be merged in larger units with a duration that equals $k_{clean} - M^{lb}_{s'} + M^{ub}_{s}$. On the other hand, we may limit the number of periods in which the surgery of an infected patient is allowed to start. In order to do so, we require that idle periods are not yet merged into larger cleaning blocks and that the number of idle periods in slot s is smaller than k_{clean}. Let i be the infected type and i' represent an idle period, then we have for each slot s in which at least one infected patient has to be scheduled: $\forall p : M_s^{lb} \leq p \leq M_s^{ub} - |N_{is}| \cdot k_i - |N_{i's}|$: $x_{ips} = 0$.

5.5.2.3 Identifying allowed surgery starting times

Let us illustrate by means of an example that not only the allowed surgery starting times of infected patients can be limited. Suppose we have to schedule the three surgeries that are depicted in Figure 5.7 (a) in the empty operating room slot s. We may question whether the surgery of type 4 is allowed to start on period 6, as represented in Figure 5.7 (b). Fixing $x_{4,6,s} = 1$, however, results in dividing the slot in two residual time sections: period 1 up to period 5 and period 10 up to 11. When we refer to knapsack A for the first time section and knapsack B for the second section, we can solve the question whether the surgery of type 4 can start on period 5 by solving a multiple knapsack problem. In this multiple knapsack problem, we are only interested in finding a feasible solution: is it possible to assign the remaining surgeries to the knapsacks so that the capacity of the knapsacks is not violated? Figure 5.7 shows that it is not possible to precisely fit a surgery of type 4 and type 5 into the knapsacks, so that we conclude that the decision variable $x_{4,6,s}$ must be equal to 0. Note that only the surgery duration is taken into account during the assignment process and that other constraints (e.g. instrument use) are relaxed. The solution procedure of the multiple knapsack problem is executed for each decision variable that is added to the formulation.

5.5.3 Iterated MILP

In the iterated MILP, we start from the preprocessed MILP and iteratively fix the starting times of a particular set of surgeries. We may expect that this policy enhances the solvability of the new problem as the solution space has decreased in size. In particular, three decisions have to be taken. First, we have to decide on the set of slots in which no fixation of surgery starting

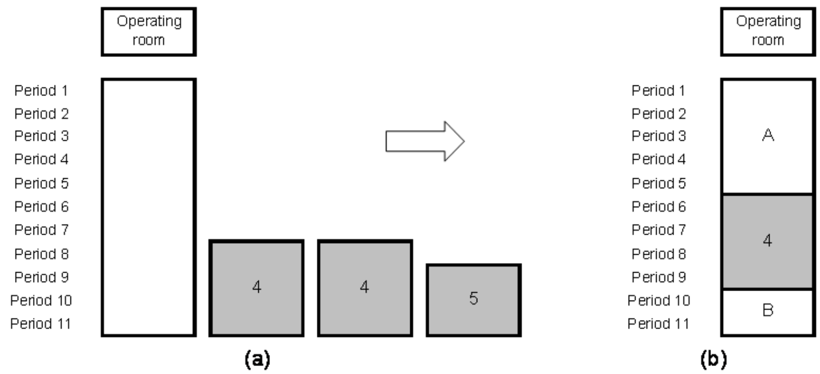

Figure 5.7: Identifying allowed surgery starting times by solving multiple knapsack problems

times will take place by means of a predetermined probability $prob_1$. If this probability equals 1, we end up in the setting of the preprocessed MILP in which no particular surgery starting times are fixed, except those that are not feasible. Second, a probability has to be determined that indicates the percentage of surgeries that will be fixed for each of the remaining slots ($prob_2$). Third, we have to indicate the appropriate solution time for one iteration. In Section 5.6, we provide a thorough testing of the influence of the solution parameters on the solution quality based on 36 configurations. In short, it turns out that, regardless of the imposed time limit of 5, 10 or 15 seconds per iteration, a setting of $prob_1 = 0.1$ and $prob_2 = 0.2$ leads to superior results. Therefore, we adapt this setting in the iterated MILP and vary the running time of the iterations proportionally between 5, 10 and 15 seconds.

5.5.4 Branch-and-Price

Instead of introducing decision variables that correspond to the surgery starting time of an individual surgery, we can also formulate decision variables in terms of sequenced groups of surgeries. In the subsequent sections, we will refer to this new type of variables as *patterns* or *columns*. In particular, a column can be seen as a sequenced group in which all surgeries for one specific slot are represented. Choosing the variable hence implies that the starting times of its constituting surgeries are known.

Let z_{st} denote a binary decision variable that equals 1 if column t is chosen for slot s. Let a^e_{pst} represent the number of instruments of type e in use at period p when column t is chosen for slot s and let a^j_{pst} $(j \in J : j \geq 5)$ indicate how many bed spaces of PACU 1 $(j = 5)$ or PACU 2 $(j = 6)$ are needed in period p when column t is chosen for slot s. Next to these resource parameters, we also have a cost parameter c^j_{st} that indicates how much α_j will increase when column t is chosen for slots s $(j \in J : j \leq 4)$. T_s represents the set of feasible columns for surgeon s. Whether a column is feasible or not depends on two factors. First, there is the obligatory additional cleaning of the operating room after the surgery of an infected patient (MRSA) that has to be satisfied. Second, patients with incomplete pre-surgical tests have to receive a surgery starting time that does not precede the reference period *testlimit*. Whenever at least one of these restrictions is violated, the pattern is infeasible. The necessary information needed to check the restrictions is entirely determined by the sequence in which surgeries are performed. Recall from Section 5.5.1 that the initial starting time of a slot M^{lb}_s is given by the known master surgery schedule, that $PACU1cap$ ($PACU2cap$) represents the number of bed spaces available in PACU 1 (PACU 2) and that cap_e denotes the available capacity of instrument e. The SCSP can now be stated as the MILP model described by Expressions (5.21) to (5.29).

$$MIN \quad \sum_{j \in J} w_j \cdot \left(\frac{\alpha_j - bestvalue_j}{worstvalue_j - bestvalue_j} \right) \tag{5.21}$$

$$S.T. \quad \sum_{s \in S} \sum_{t \in T_s} c^j_{st} \cdot z_{st} - \alpha_j = 0 \qquad \forall j \in J : j \leq 4 \tag{5.22}$$

$$\sum_{s \in S} \sum_{t \in T_s} a^j_{pst} \cdot z_{st} - \alpha_j \leq 0 \qquad \forall p \in P,\ \forall j \in J : j \geq 5 \tag{5.23}$$

$$\sum_{s \in S} \sum_{t \in T_s} a^e_{pst} \cdot z_{st} \leq cap_e \qquad \forall e \in E,\ \forall p \in P \tag{5.24}$$

$$\alpha_5 \leq PACU1cap \tag{5.25}$$

$$\alpha_6 \leq PACU2cap \tag{5.26}$$

$$\sum_{t \in T_s} z_{st} = 1 \qquad \forall s \in S \qquad (5.27)$$

$$z_{st} \in \{0, 1\} \qquad \forall s \in S, \forall t \in T_s \qquad (5.28)$$

$$\alpha_j \geq 0 \qquad \forall j \in J \qquad (5.29)$$

Constraint set (5.22) and (5.23) are both introduced to determine the values of the auxiliary variables α_j. While for objective $j \in J : j \leq 4$ the value of α_j is determined by adding the values of c^j_{st} when the appropriate column is chosen, this approach cannot be used when $j \in J : j \geq 5$. When a surgery schedule, for instance, consists of two columns and each column has a peak demand for bed spaces in PACU 1 equal to 4, it is not guaranteed that $\alpha_5 = 4 + 4 = 8$. Actually, $\alpha_5 = 8$ only occurs when both peak demands are established simultaneously for at least one period. Constraint set (5.24) ensures that the simultaneous demand for medical instruments cannot exceed the available capacity. Note that the demand for medical instruments also depends on the required sterilization duration. Not only the number of instruments is limited, also the number of bed spaces provided in PACU 1 and PACU 2 is restricted. Inequality (5.25) and (5.26) respectively state that the peak number of bed spaces in PACU 1 and PACU 2 cannot exceed the available capacity. Constraint set (5.27) specifies that for each surgeon exactly one column has to be chosen. Finally, the decision variables z_{st} are restricted by constraint set (5.28) to be binary, whereas the auxiliary variables α_j are restricted to be non-negative (5.29).

We are able to show that the LP relaxation of the formulation stated by Expressions (5.21) to (5.29), i.e. the z-formulation, is at least as strong as the formulation that is stated by Expressions (5.5) to (5.20), i.e. the x-formulation. Although we omit to formally prove this statement in the dissertation's text, we provide a general idea of the proof's structure. First, we have to show that any solution $\hat{\mathrm{z}}$ of the LP relaxation of the z-formulation can be transformed to a solution $\hat{\mathrm{x}}$ of the LP relaxation of the x-formulation. Second, we have to indicate the feasibility of solution $\hat{\mathrm{x}}$ with respect to the constraints (of the x-formulation's LP relaxation). Third, we have to prove that the transformation of solution $\hat{\mathrm{z}}$ to solution $\hat{\mathrm{x}}$ results in the same objective value. Finally, we have to report that at least one instance can be found in which the LP relaxation of the z-formulation is stronger than the LP relaxation of the x-formulation. In Section 5.6.4.2.1, we provide numerical results that affirm this final notion.

When there is a substantial number of surgeries, the number of columns easily explodes. This leads to an enormous set of decision variables that cannot be handled efficiently by a commercial solver. *Column generation*, on the contrary, works only with a sufficiently meaningful subset of variables to solve the LP relaxation of the combinatorial optimization problem at hand (see Section 5.5.4.1). In order to obtain integer variables, though, we have to embed the column generation approach in an enumerative branch-and-bound framework (see Section 5.5.4.2). This methodology is often referred to as *branch-and-price*. In Section 5.5.4.3, we finally address some speed-up techniques to increase the algorithm's performance. The general course of a generic branch-and-price procedure is shown in Algorithm 5.2. Although we do not cover this pseudo-code in detail, it may clarify many concepts and relations that will be discussed in the next three sections and as such situate their contribution in this advanced methodology.

5.5.4.1 Column generation

Column generation is a technique that decomposes a combinatorial optimization problem into a master problem and a subproblem [56]. This decomposition, which constitutes the spine of the column generation optimization loop, is depicted in Figure 5.8. The master problem represents an LP formulation that is similar to the MILP model that was introduced in Section 5.5.4. Since this master formulation is solved using only a subset of all the existing columns, we will refer to this problem as the *restricted master problem* (RMP). More variables are only added to the RMP when needed (i.e. when the solution to the RMP does not equal the LP relaxation of the problem when all existing columns would be considered) by solving a subproblem or *pricing problem*. When we are able to generate a column in the pricing problem that exhibits a negative reduced cost, this column should be added to the subset of variables that is added to the RMP and the optimization

Algorithm 5.2 Branch-and-price

```
apply heuristic to find initial solution;
if (solution found) then
   register schedule;
   upper_bound ← best solution found;
   initiate master with p columns from initial solution and p supercolumns;
else
   upper_bound ← +∞;
   initiate master with p supercolumns;
end if
l ← 0;
while (l ≥ 0) do
   LP_opt_found ← FALSE;
   while (LP_opt_found=FALSE) do
      LP_opt_found ← TRUE;
      upper_bound ← SOLVE-MASTER-LP();
      for (k = 1 to p) do
         RC_k ← FIND-NEW-COLUMN(k);
         if (RC_k < 0) then
            add new column to master;
            LP_opt_found ← FALSE;
         end if
      end for
   end while
   continue ← TRUE;
   while (continue=TRUE) do
      if (LP_opt ≥ upper_bound) then
         while (all branches on level l explored) do
            l ← l − 1; {backtrack}
         end while
         explore next branch on level l;
         add corresponding branching restriction;
         continue ← FALSE;
      else if (fractional solution) then
         l ← l + 1; {branch one level further}
         add new branching restriction;
         continue ← FALSE;
      else if (integral solution) then
         register schedule;
         upper_bound ← LP_opt;
      end if
   end while
end while
```

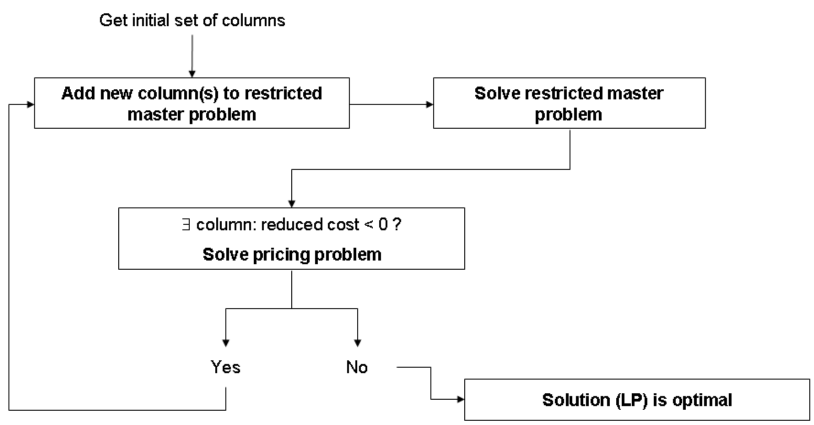

Figure 5.8: Visualizing the column generation optimization loop

loop should be repeated. However, when no column prices out (i.e. has a negative reduced cost), the solution to the RMP also optimizes the LP relaxation when all variables would be considered and the column generation loop terminates. In the next two sections, we apply the column generation technique to the SCSP and discuss the RMP (see Section 5.5.4.1.1) and the pricing problem (see Section 5.5.4.1.2) in detail.

5.5.4.1.1 Restricted master problem

Some modifications are needed to the formulation stated by Expressions (5.21) to (5.29) of Section 5.5.4 in order to represent the RMP of interest. First, we reformulate the objective function as represented by Expression (5.30).

$$\left(\sum_{s\in S}\sum_{t\in T_s} c_{st}\cdot z_{st}\right)+\sum_{j\in J:j\geq 5}\frac{w_j\cdot\alpha_j}{worstvalue_j-bestvalue_j}-\sum_{j\in J}\frac{w_j\cdot bestvalue_j}{worstvalue_j-bestvalue_j} \tag{5.30}$$

We distinguish between the objectives that are entirely determined within a column ($j\in J: j\leq 4$) and those that only can be determined by aggregating the columns into a surgery schedule ($j\in J: j\geq 5$). For the latter category of objectives, we maintain the auxiliary variable α_j, whereas these variables and the corresponding constraint set (5.22) are dropped for the former category. The cost of column t for slot s with respect to objectives $j \in J : j \leq 4$ is now incorporated in the data parameter c_{st}. This parameter, which is defined as $c_{st} = \sum_{j \in J: j \leq 4} \frac{w_j \cdot c^j_{st}}{worstvalue_j - bestvalue_j}$, is determined while solving the pricing problem and takes the appropriate normalization and weights into account. Since the last term in Expression (5.30) is a constant, it is neglected during optimization and reincorporated afterwards in order to obtain a correct solution value. A detailed derivation of Expression (5.30) from Expression (5.21) is given in Appendix A.

Next to the modification of the objective function and the elimination of constraint set (5.22), we also relax the integrality constraints expressed in (5.28) and add the constraints of set (5.29) only for objective $j \in J : j \geq 5$.

5.5.4.1.2 Pricing problem

The pricing problem deals with generating columns that are characterized by a negative reduced cost. When we assume that ρ_{jp}, π_{ep} and λ_s respectively represent the dual prices of restrictions (5.23), (5.24) and (5.27), the reduced cost of a column t for a slot s (RC_{st}) is specified by Equation (5.31). When such a column is found, it should be added to the subset of variables and the RMP should be re-optimized.

$$RC_{st} = c_{st} - \lambda_s - \sum_{j \in J: j \geq 5} \sum_{p \in P} (\rho_{jp} \cdot a^j_{pst}) - \sum_{e \in E} \sum_{p \in P} \pi_{ep} \cdot a^e_{pst} \tag{5.31}$$

Since we can only obtain the dual prices of the restrictions when a feasible solution is found for the RMP, the RMP is initiated with a set of binary dummy variables or supercolumns. In particular, a supercolumn is added for each slot s and is similar to an ordinary column, except that it does not consume any resources. As such, their value can easily be adapted in order to satisfy the convexity constraints (Expression 5.27) and hence to ensure feasible solutions. This, however, comes at a very high cost since a schedule that is built with supercolumns is unrealistic in nature. Eventually, we have to find a schedule in which no supercolumns are selected.

There is no need to solve the pricing problem for every $s \in S$. We could resolve the RMP whenever at least one column t for a certain slot s is found with $RC_{st} < 0$. However, many variations are allowed in order to solve the LP relaxation to optimality. When multiple columns price out, one may choose on the number of columns to be added to the RMP. In Section 5.6, we compare several pricing strategies on their computational efficiency. In the remainder of this section, we will elaborate on two approaches to solve the pricing problem, namely a dynamic programming approach (see Section 5.5.4.1.3) and an MILP approach (see Section 5.5.4.1.4). They both generate, for a given slot, the column that results in the most negative reduced cost.

5.5.4.1.3 Solving the pricing problem: Dynamic programming

Dynamic programming (DP) is a solution methodology that decomposes a problem into a nested family of smaller and hence more tractable subproblems [19]. Let N_s denote the set of surgeries that have to be performed in slot s. In order to solve the pricing problem of a slot s, we then distinguish between $|N_s| + 1$ stages ($0 \leq g \leq |N_s|$). The numerical index of a stage represents the number of surgeries that are already scheduled at that point. Each stage has a number of states associated with it that indicate the types of surgeries that are already scheduled. Since multiple patients may have the same surgery type (i.e. there are duplicates), describing states in terms of surgery types diminishes the symmetry and hence contributes to the computational efficiency of the algorithm [253]. In Table 5.2, the enumeration of stages and states is illustrated by means of an example.

In the example, 4 surgeries need to be scheduled for slot s ($|N_s| = 4$), namely one surgery of type 1, two surgeries of type 2 and one surgery of type 3. This results in 5 stages and 12 states. In general, stage 0 only contains the empty state $h^{\emptyset}$, whereas stage $|N_s|$ only consists of a state in which all surgeries

Table 5.2: Enumerating stages and states of a dynamic programming example.

Stage	States
0	{}
1	{1}, {2}, {3}
2	{1,2}, {1,3}, {2,2}, {2,3}
3	{1,2,2}, {1,2,3}, {2,2,3}
4	{1,2,2,3}

are scheduled. It should be clear that the transition from a state h at stage g to a state h' at stage $g+1$ corresponds to adding one specific surgery of type i to the surgery schedule. In Table 5.2, the transition $\{1\} \rightarrow \{1,2\}$, for instance, corresponds with starting a surgery of type 2 ($i = 2$) immediately after the finish of the surgery of type 1. Note that $h \rightarrow h'$ is only allowed when the surgeries at state h are a subset of those at state h' ($h \subset h'$). Let H_g represent the set of states at stage g. In order to determine for slot s a column t that exhibits the most negative reduced cost (RC_s^*), a recursive function is then formulated as follows:

$$RC_s^* = \min_{h \in H_1} \Big\{ C(h^{\emptyset}, h) + F_1(h) \Big\} - \lambda_s \tag{5.32}$$

$$F_g(h) = \min_{h' \in H_{g+1} : h \subset h'} \Big\{ C(h, h') + F_{g+1}(h') \Big\} \tag{5.33}$$

In general, $F_g(h)$ represents the minimum cost incurred for the completion of the surgery schedule with surgery types that still have to be scheduled during stages $g+1$ up to stage $|N_s|$, given that state h at stage g is realized. Note that for state $h \in H_{|N_s|} : F_{|N_s|}(h) = 0$. When we return to Table 5.2 and assume that state $\{1,2\}$ at stage 2 is realized, we can complete the surgery schedule by either adding the sequence $2 \prec 3$ (i.e. adding a surgery of type 2 at stage 3 and a surgery of type 3 at stage 4) or $3 \prec 2$ (i.e. adding a surgery of type 3 at stage 3 and a surgery of type 2 at stage 4). Once both alternatives are evaluated, $F_2(\{1,2\})$ is set equal to the cost of the alternative characterized by the lowest cost. During the algorithmic search, a state h at stage g can possibly be visited multiple times. The state $\{1, 2\}$, for instance, can be reached from two states at stage 1, namely $\{1\}$ and $\{2\}$. Saving the values of $F_g(h)$ during the enrolment of the algorithm consequently avoids the need to recompute subproblems that already have been solved once. Michie [192] referred to this concept as *memoization*.

The transition from state h to state h' comes at a cost equal to $C(h, h')$ and reflects the cost for starting a surgery of type i at period p, i.e. when all surgeries represented in state h are already performed. $C(h, h')$ consists of three major cost components. First, there are the infeasibility costs. In particular, costs rise to infinity (∞) when violations occur with respect to infections or pre-surgical tests. Second, $C(h, h')$ incorporates costs associated with the objectives $j \in J : j \leq 4$ due to the start of the new surgery. Finally, $C(h, h')$ also reflects costs that stem from the non-positive dual prices of restrictions (5.23) and (5.24). Since the outcome of $C(h, h')$ is highly conditional, we summarize its calculation using pseudo-code stated in Algorithm 5.3. In this code, k_i, l_i and m_i respectively denote for a surgery of type i its surgery duration, stay in PACU 1 and stay in PACU 2 (expressed in periods). P^{ub} indicates the period that coincides with the closure of the day-care center and $ster_e$ equals the number of periods needed to sterilize an instrument of type e.

The dynamic programming formulation of Equations (5.32) and (5.33) is accurate for optimizing pricing problems in which infections do not occur. This formulation, however, does not hold when infections come into play. One problem, for instance, arises with the application of the memoization feature. Let us illustrate this using the example introduced in Table 5.2 once again. Suppose we arrive in state $\{1, 2\}$ at stage 2 and none of the patients is infected. Furthermore $F_2(\{1,2\})$ is already calculated and equals the cost associated with the sequence $3 \prec 2$. No matter how we arrive in state $\{1, 2\}$

Algorithm 5.3 Calculation of the transition cost $C(h, h')$

/*Incorporate infeasibility costs*/
if *Infeasible transition* **then**
  $C(h, h') = \infty$
else
  /*Incorporate objective costs*/
  $C(h, h') = 0$
  if *Child* **then**
    $C(h, h') += p \cdot w_1 \,/\, (worstvalue_1 - bestvalue_1)$
  end if
  if *Prioritized patient* **then**
    $C(h, h') += p \cdot w_2 \,/\, (worstvalue_2 - bestvalue_2)$
  end if
  if *Travel patient scheduled before reference period* **then**
    $C(h, h') += w_3 \,/\, (worstvalue_3 - bestvalue_3)$
  end if
  if *Recovery needed after closing time day-care center* **then**
    $C(h, h') += (p + k_i + l_i + m_i - 1 - P^{ub}) \cdot w_4 \,/\, (worstvalue_4 - bestvalue_4)$
  end if
  /*Incorporate costs dual prices*/
  $C(h, h') -= \sum_{p'=p+k_i}^{p+k_i+l_i-1} \rho_{1p'} + \sum_{p'=p+k_i+l_i}^{p+k_i+l_i+m_i-1} \rho_{2p'} + \sum_{e \in E} \sum_{p'=p}^{p+k_i+ster_e} \pi_{ep'}$
end if

(i.e. by $\{\} \rightarrow \{1\} \rightarrow \{1,2\}$ or $\{\} \rightarrow \{2\} \rightarrow \{1,2\}$), $F_2(\{1,2\}$ can always be used as the optimal value of the subsequent subproblem. However, when the surgery of type 1 represents an infected patient, the additional cleaning time due to the infection equals 1 period and the surgeries of type 2 represent idle periods, it would be incorrect to use $F_2(\{1,2\})$ as the optimal value of the subproblem according to the path $\{\} \rightarrow \{2\} \rightarrow \{1,2\}$, since the infected surgery would immediately precede a surgery of type 3 instead of the obliged idle period. One other problem of scheduling infected patients is that such decisions do not only restrict the states that can be reached in the next stage, but also those in further stages (i.e. as long as the obliged cleaning session is not finished). In order to incorporate infections accurately, Equations (5.32) and (5.33) should be modified. A formulation of this generalized dynamic programming formulation is described in Appendix B.

Registering the minimum costs entails an important contribution to the computational efficiency and reduces the running time of the algorithm. In order to understand the efficiency of the DP algorithm, we will identify the appropriate complexity class. We assume that no patients $n \in N_s$ can be identified with the same surgery type. It should be noted that this assumption leads to a worst-case analysis, since duplicate surgeries would further reduce the calculation effort needed to solve the pricing problem. We will focus on the number of recursive calls, which clearly depends on the problem size $|N_s|$, in order to determine the running time of the algorithm. Since a recursive call can be interpreted as a visit to a state at a further stage, defining the running time boils down to determining how much progressive state visits are executed during the algorithmic search. In particular, two components need to be calculated. On the one hand, we have to determine the number of states present at stage g $(= |H_g|)$. On the other hand, we have to determine the number of visits to a state h at stage g. We assume that no visit is required to the empty state $h^{\emptyset}$ at stage 0, since this is the starting point of the algorithm. With respect to the first component, the number of states at stage g is calculated as $|N_s|!/[(|N_s| - g)! \cdot g!]$. Since the state space is divided into $|N_s| + 1$ stages, the total number of states needed to solve the entire pricing problem is equal to $\sum_{g=0}^{|N_s|} |N_s|!/[(|N_s| - g)! \cdot g!]$.

Since this number actually represents the enumeration of all possible subsets of surgeries, it is equal to $2^{|N_s|}$. With respect to the second component, the number of visits to a state at stage g equals g. This is a consequence of saving intermediate results, i.e. a consequence of the memoization feature. Note that when this feature is turned off, the number of visits to a state at stage g increases to $g!$. This latter approach would result in a complete enumeration of all the paths and could hence be seen as a brute-force approach with a running time equal to $O(n!)$. Since we do apply the memoization feature, the number of computational steps needed to solve a pricing problem of size $|N_s|$ can be determined through Equation 5.34.

$$\sum_{g=0}^{|N_s|} g \cdot \frac{|N_s|!}{(|N_s|-g)! \cdot g!} = |N_s| \cdot \frac{1}{2} \cdot 2^{|N_s|} = |N_s| \cdot 2^{|N_s|-1} \tag{5.34}$$

From Equation 5.34, we may conclude that the dynamic programming algorithm runs in exponential time. Although algorithms with an exponential running time are globally considered to be inefficient, it should be noted that if the problem size is small, the complexity class might not matter very much [259]. This implies that satisfying computational results can still be obtained for the pricing problem since $|N_s|$ is limited to 15 surgeries (see Section 5.6). Moreover, although the running time is exponential, it is far more efficient than the factorial approach. Solving a pricing problem of size $|N_s| = 15$ results in 245760 computational steps in the former case, whereas about 3.5×10^{12} steps are needed in the latter case.

5.5.4.1.4 Solving the pricing problem: MILP

Alternatively, we can also state the pricing problem as an MILP and solve it using a commercial solver. The formulation is actually a restricted version of the preprocessed MILP model that was introduced in Section 5.5.1.

There are two main reasons why we developed, next to the dynamic programming algorithm, this second pricing approach. First, we want to use it as a benchmark in order to investigate the efficiency of the dynamic programming formulation (see Section 5.6). Second, when the MILP pricing model itself turns out to perform well, we can use it in the branch-and-price algorithms in order to branch on the column variables z_{st}. When we prevent columns to price out multiple times only by making slight modifications (e.g. changing cost coefficients), the structure of the pricing problem remains stable. One major inconvenience that is related to branching on the column variables, though, is that the pricing structure has to be adapted. This, however, is a complicated task with respect to the dynamic programming formulation, whereas this is easily done for the MILP pricing model.

5.5.4.2 Branching tree

Since the column generation loop optimizes the LP relaxation of the SCSP, the optimal values for the column variables do not necessarily equal 0 or 1. In order to get integer values for these column variables, we have to embed the column generation optimization loop in an enumerative branch-and-bound framework. In this section we elaborate on the choice of the branching strategy (see Section 5.5.4.2.1) and the branching schemes (see Section 5.5.4.2.2).

5.5.4.2.1 Branching strategy

In Section 5.4.1, we already mentioned the distinction between a depth-first or backtracking strategy and a best-first or skiptracking strategy and favored the use of a depth-first strategy. In the computational experiment of Section 5.6, however, we implement a depth-first as well as a best-first strategy for the branch-and-price approaches. The reason is threefold. First, we know that a reformulation of the SCSP in terms of columns (i.e. a huge number of variables) results in a tight relaxation (see Section 5.5.4). As a consequence, the search of a best-first algorithm may finish in time. Second, feasible solutions can be encountered even when a best-first algorithm ends prematurely. This is the case when the intermediate solution of the RMP during the column generation loop is formed by integer variables. Third, best-first algorithms search the tree in an unstructured way. This diversity and variety can be exploited to improve solution quality (see Section 5.6).

5.5.4.2.2 Branching schemes

In Section 5.5.4.1.4, we proposed to branch on the column variables in order to partition the solution space and eliminate the occurrence of fractional column variables. This implies that we need to identify a column $z_{st} : 0 < z_{st} < 1$ and fix z_{st} either to 1 (left branch) or 0 (right branch). However, thorough testing of the MILP pricing algorithm revealed a weak performance (see Section 5.6). Hence we limit the focus on branching schemes that do not harm the structure of the pricing problem. In particular, four binary branching schemes are presented and implemented in which branching restrictions will be formulated in terms of the individual surgeries. It can be shown that these schemes are complete.

In a first scheme, we fix a surgery of type i to start on a period p for a slot s in the left branch, whereas the contrary is true for the right branch. Since there are far more columns for which the proposition of the right branch holds, this branching scheme results in a highly unbalanced tree. Although this restricts the ability to prove the optimality of a solution, it should allow for a quick detection and improvement of feasible solutions. The second branching scheme is similar to the first, except that now a surgery of type i for slot s should be in process on period p (left branch). The opposite obviously holds for the right branch. Although the freedom to slightly shift the starting period of the surgery type should favor the balancing of the tree, this branching scheme is still unbalanced. Therefore, we thought of a third branching scheme in which a surgery of type i for slot s has to be started before or on period p (left branch), whereas it should start after period p in the right branch. In this branching scheme, however, a problem occurs when multiple patients have the same type of surgery since the branching restriction would apply to all patients with a surgery type equal to i. Therefore we specify the branching restrictions on the patient level instead of the surgery type level. This implies, for instance, that the surgery of patient n for slot s has to be started before or on period p (left branch). Moreover, precedence relations between patients with a common surgery type are introduced in order to avoid symmetry. Next to the three time-based branching schemes, we also introduce a sequence-based branching scheme. In particular, we oblige a surgery type to be scheduled in a specific position, e.g. a surgery of type i has to be scheduled as the fifth surgery (left branch). In the right branch, only columns are taken into account in which the surgery type does not appear on the specific position. We should mention that many other branching schemes, for instance hybrid or non-binary schemes, can be developed and tested. This, however, constitutes an area for future research.

The information needed in order to specify the appropriate branching restriction is determined by comparing two fractional columns for a common slot. We do have to decide, though, which columns to pick and which $i-p$ combination to choose when the surgery sequences of the fractional columns differ on multiple places. Intuitively, it seems reasonable to select columns characterized by the most fractional value (i.e. close to 0.5 and thus balanced) or highest value (i.e. close to 1 and thus an extremely valuable column). Preliminary computational results indicated that selecting the columns with the highest fractional value and choosing the $i-p$ information that corresponds with the earliest conflict, performed better than a branch-and-price approach in which choices (most fractional value, highest fractional value, earliest conflict and latest conflict) were made randomly.

5.5.4.3 Speed-up techniques

In order to upgrade the performance of the branch-and-price algorithms, several speed-up techniques can be developed and implemented. The techniques introduced in this section consist of an initial solution, a lower bound in the column generation optimization loop and the elimination of columns along the branching tree.

5.5.4.3.1 Initial solution

The expected contribution of introducing an initial solution is twofold. On the one hand, it enables the algorithm to fathom branches that lead to a solution value that is larger than the initial solution value (depth-first). On the other hand, it augments the probability of finding at least one feasible solution to the SCSP. This last feature is especially complementary with the best-first branching strategies.

We run the iterated MILP procedure that is discussed in Section 5.5.3 in order to obtain a heuristic initial solution. However, we modified some parameter settings as the total running time of this initial solution procedure is limited to 60 seconds. Each iteration runs now for maximally 10 seconds. Obviously, each iteration is accompanied by a different fixation pattern. Recall that the settings of the parameters are chosen based on a computational experiment that comprises 36 configurations (see Section 5.6).

5.5.4.3.2 Lagrangian lower bound

One of the well-known difficulties with column generation is that a large number of iterations is required in order to prove that the RMP is solved to optimality. In the literature, one often refers to this phenomenon as the tailing-off effect [280]. A lower bound, though, can be specified in order to prematurely stop the column generation optimization loop without any risk of missing the LP optimum [125]. The calculation of the lower bound, which is also known as the Lagrangian lower bound, starts with solving the RMP. Next, for each slot $s \in S$, a pricing problem is solved in which the column with the most negative reduced cost is determined. When the pricing problem of slot s results in a column t: $RC_{st} < 0$, its value is added to the solution value of the RMP. Remark that this summation decreases the LP solution value and that at most $|S|$ summations are performed. If the modified LP solution value is larger than the best integer solution value that was already obtained along the tree, the column generation optimization loop can be safely terminated.

5.5.4.3.3 Column elimination

When we focus on the depth-first branching strategy, columns that have been generated along the tree may become superfluous at a certain point in time due to the active set of branching restrictions. Loading the RMP with a considerable amount of variables (even when they are set equal to 0) increases the required solution time. It should hence be beneficial to remove the superfluous columns from the list. With respect to the best-first branching strategy, a trade-off exists between the time gained by solving a RMP with few columns and the time needed to regenerate columns that were already deleted during the tree generation process. In Section 5.6, though, we point at the benefits of column elimination for intertwining best-first branch-and-price algorithms with an intermediate and recurrent heuristic procedure without losing the exact nature of the algorithms.

5.6 Computational experiment

A detailed computational study of the algorithmic procedures and some of their peculiarities constitutes the focus of this section. After a short introduction of the test set that underlies the test results in Section 5.6.1, we proceed in Section 5.6.2 to a discussion of the calculation of the extreme values ($worstvalue_j$ and $bestvalue_j$) that are needed to normalize the objectives. In Section 5.6.3 we study the computational performance of the dedicated branch-and-bound procedures that were developed in Section 5.4. Finally, we turn our interest in Section 5.6.4 to the MILP procedures that were discussed in Section 5.5.

All algorithms, which are truncated after 300 seconds or five minutes of running time, are written in MS Visual C++.NET and are linked with the ILOG CPLEX 10.2 optimization library when needed [138]. Limiting the running time of the algorithms is necessary as the human planner often wants to compare multiple schedules and change the settings of the problem to study what-if questions (see Chapter 6). The computational experiment was executed on a 2.33 GHz Pentium 4 PC with 1 GB RAM and the Windows XP operating system.

5.6.1 Generating test instances

The test set consists of 224 instances and is built with data from the surgical day-care center of the UZ Leuven Campus Gasthuisberg (Belgium). For ease of reference, we recapitulate some of the specific features of this freestanding ambulatory unit. The center opens at 7 a.m. and closes at 7 p.m. and the operating theater comprises 8 operating rooms, opened between 8 a.m. and 5 p.m. The assignment of disciplines and staff to the operating rooms is fixed and imposed by the master surgery schedule. Furthermore, there are 8 bed spaces in PACU 1 and 12 bed spaces in PACU 2. The daily number of surgeries performed at the day-care center is volatile and ranges from 40 to 70. However, the number of surgeries that is performed in a single slot is less than 15.

We use patient-related data gathered in 2005 to generate the instances and make a distinction between 17 of the most important medical disciplines or entities (e.g. orthopaedics, gynaecology, dermatology,...). For each medical discipline and their surgery types we know the probability of occurrence. Furthermore, for each surgery type, the planned surgery duration (including anaesthesia, skin-to-skin time, after care and cleaning), the planned time in PACU 1 and PACU 2, the required bottleneck instruments and the corresponding sterilization time is known. All time-related data are expressed in five-minute periods. Probabilities concerning children, priority, travel distance, incomplete pre-surgical tests and MRSA infections, however, are only occasionally registered up to now and hence suggested by the head nurse, based on experience (expert data).

We varied the size of the instances (i.e. 20, 25, 30,... up to 85 surgeries) and added some structure using design patterns that differ on 3 levels, as illustrated in Figure 5.9. First, a decision is made on the surgery workload of a slot. On the one hand, large fluctuations may occur between their workload. On the other hand, each slot may have a comparable number of surgeries to perform. Second, we distinguish between master surgery schedules with frequent switches of slots in the operating rooms and schedules in which a switch is rare. Third, the objectives can be equally weighted or not. The sum of the weights, however, always equals 1. Note that these design patterns have nothing to do with the columns or patterns of the column generation approach of Section 5.5.4.

	Level 1	Level 2	Level 3
Pattern 1	*depth*	*rare switch*	= *weight*
Pattern 2			≠ *weight*
Pattern 3		*frequent switch*	= *weight*
Pattern 4			≠ *weight*
Pattern 5	*width*	*rare switch*	= *weight*
Pattern 6			≠ *weight*
Pattern 7		*frequent switch*	= *weight*
Pattern 8			≠ *weight*

Figure 5.9: Representation of the design patterns used for the generation of test instances

We may wonder whether the structure and the size of an instance significantly determines its solvability or whether this solvability depends on random and uncontrolled factors. Figure 5.10 divides the test set according to the various design features and indicates to what extent each subgroup of instances is solved to optimality within 60 seconds using the basic MILP procedure of Section 5.5.1. Figure 5.10 clearly shows that the number of surgeries that has to be scheduled negatively influences the probability to find an optimal solution. However, not only the number of surgeries affects the solvability. There also seems to be a major fluctuation based on the design patterns. We see that instances that are generated in depth (level 1) are harder to solve. Indeed, the number of schedules resulting from, e.g., sequencing 8 surgeries for one slot is 70 times larger than the number of schedules that should be evaluated when two slots have to perform 4 surgeries each. Furthermore, we notice that the presence of slot switches in an operating room facilitates the search to optimality. An analogous explanation applies in this case. Finally, instances that are characterized by unequal weights tend to be slightly easier to solve than those with equal weights (level 3). The diversification of the weights may enable the solution procedure to exhibit features of a sub-optimal lexicographic methodology. This means, in the extreme, that the problem is optimized for the most important (largest

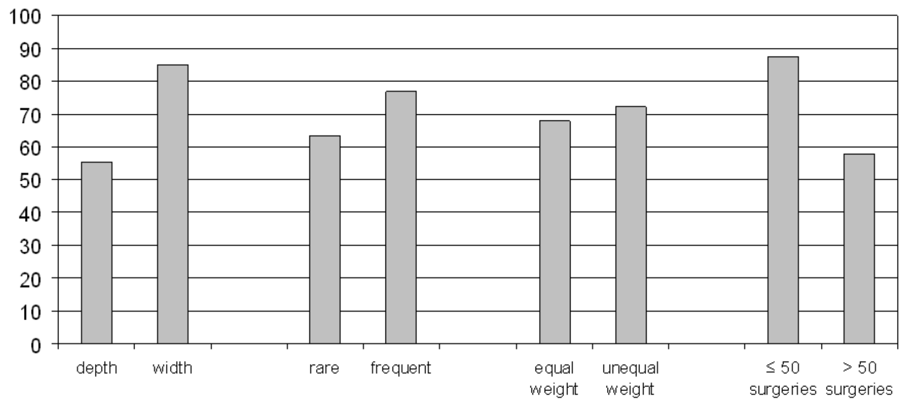

Figure 5.10: Examining the percentage of instances that is solved to optimality within 60 seconds using the basic MILP based on the characteristics of their underlying design pattern and size

weight) objective first and that the solution space is limited to schedules that set this objective to its best value. Then the next most important objective is optimized and the solution space is consecutively limited. When weights take proportions so that trade-offs are unlikely to happen, we somehow create an equivalent situation which is easier to solve since the number of schedules that has to be evaluated is limited.

For about 1% of the instances, we still cannot prove optimality (truncation after 96 hours) using the procedures that were developed in this chapter. For these instances, we take the value of the current best node in the tree that still had to be explored as a lower bound for the optimal value to calculate the appropriate solution gaps.

5.6.2 Calculating the extreme objective values

As described in Section 5.2, the parameters $bestvalue_j$ and $worstvalue_j$ are of major importance for building the objective function. These extreme values for the objectives are obtained by solving the SCSP using variants of the preprocessed MILP model of Section 5.5.2. Now, though, we have to change the objective function, both in sense and in formulation. For each objective

j the model is solved twice, namely minimizing α_j to obtain $bestvalue_j$ and maximizing α_j to obtain $worstvalue_j$. It should be noted that maximizing α_5 or α_6 respectively results in the total capacity provided in PACU 1 (=PACU1cap) or PACU 2 (=PACU2cap), while this is not necessarily a true upper bound. Therefore we solve for each objective $j \in \{5, 6\}$ a set of $|P|$ subproblems, i.e. for each period $p \in P$, which is the set of five-minute periods that constitute the working day, we solve a problem in which we maximize the number of beds used in that specific period. The worst value for the objectives $j \in \{5, 6\}$ is consecutively set equal to the highest solution value obtained over the respective $|P|$ subproblems.

The extreme values can be precisely determined by solving the resulting set of MILP formulations with the original binary decision variables x_{ips}. Unfortunately, we cannot apply this approach due to computational boundaries for instances of considerable size. Hence, we will solve the MILP formulations using continuous variables. On average, the extreme values for all objectives of an instance are obtained in 5.180 seconds. In the worst case, the required time increases to 35.296 seconds, whereas the median value is equal to 2.687 seconds. The largest part (74%) of the computation time is devoted to calculating the worst value of objective 5 and 6, as a large set of problems possibly needs to be solved.

Relaxing the decision variables may possibly lead to a bias of the extreme values with respect to their true values. Therefore, we compared the use of binary versus continuous variables for instances with less than 45 surgeries (95 instances). For at least 99% of these instances, both approaches result in exactly the same extreme values when $1 \leq j \leq 4$. For objective 5 and 6, this percentage decreases to 94%. This implies that the use of continuous variables does not harm the quality of the extreme values and the resulting intervals. Since the extreme values are obtained in an identical way for each solution approach that is tested in the chapter, this preprocessing step is omitted from the computational evaluation of the algorithmic approaches.

Table 5.3: Computational results for the basic, nested and iterated branch-and-bound procedures

		absolute solution	solution time (seconds)	solution gap (%)
Basic B&B	average	0.283	208	9.431
33% opt - 16% no sol	median	0.159	300	3.784
36% zero sol gap	st. dev.	0.332	135	13.797
Nested B&B	average	0.123	209	1.638
33% opt - 0% no sol	median	0.090	300	0.395
44% zero sol gap	st. dev.	0.114	133	3.526
Iterated B&B	average	0.106	300	0.557
0% no sol	median	0.082	300	0.000
66% zero sol gap	st. dev.	0.098	0	1.229

5.6.3 Results: branch-and-bound

This section studies the computational performance of the dedicated branch-and-bound procedures of Section 5.4. Table 5.3 summarizes the results for the basic, nested and iterated branch-and-bound procedures.

None of the exact branch-and-bound procedures succeeds in proving the optimality of the solution in more than 33% of the instances, which is a rather weak performance. Since the iterated branch-and-bound algorithm is a heuristic and hence inherently unable to prove the optimality of solutions, we also consider the number of instances for which the gap between the optimal solution and the obtained solution equals 0. Since the solutions that are proven to be optimal automatically exhibit such a zero gap, this percentage should be at least the equivalent of the percentage of instances that are solved to optimality. With respect to this zero gap criterion, the basic branch-and-bound procedure (36%) is outperformed by the nested branch-and-bound procedure (44%), which is on its turn clearly outperformed by the iterated approach (66%). The modifications that are introduced in the nested and iterated algorithm to limit the number of instances for which no feasible solution can be obtained within the time limits seem to be effective as only the basic procedure cannot guarantee to find at least one feasible schedule (16%). It should be clear that lacking a feasible solution is a serious drawback for the use of an algorithm in practice.

We can question whether the difference in solution quality is rightfully represented by the percentage of instances for which the solution value is equal to the optimal value. Solutions that are close to the optimum may still be relevant and consequently influence the overall solution quality of a methodology. Therefore, we also added some statistics concerning the obtained solution gap (%) in Table 5.3. Again we notice that the nested procedure provides better results than the basic algorithm. Also the iterated algorithm performs much better compared to the nested branch-and-bound procedure. While the average gap of the basic branch-and-bound procedure (9.431%) is too large for the algorithm to be considered as efficient (and thus illustrates the difficulty in solving the SCSP), the iterated procedure features a small gap (0.557%). Note that the improvements in the solution gaps are also accompanied by decreased standard deviations. This leads to think that the nested and especially the iterated branch-and-bound procedure are more reliable in finding (more) qualitative solutions.

5.6.4 Results: MILP

Next to the dedicated branch-and-bound procedures, we are also interested in the computational results of the MILP approaches. Section 5.6.4.1 discusses the basic, preprocessed and the iterated MILP procedures, whereas Section 5.6.4.2 focuses on the branch-and-price algorithms.

5.6.4.1 Basic, preprocessed and iterated MILP

Table 5.4 lists the computational results for the basic, preprocessed and iterated MILP procedures. With respect to the percentage of instances that

Table 5.4: Computational results for the basic, preprocessed and iterated MILP procedures

		absolute solution	solution time (seconds)	solution gap (%)
Basic MILP	average	0.127	74	2.791
83% opt - 4% no sol	median	0.079	9	0.0000
86% zero sol gap	st. dev.	0.187	116	16.160
Preprocessed MILP	average	0.097	83	0.252
79% opt - 0% no sol	median	0.078	5	0.0000
85% zero sol gap	st. dev.	0.085	122	1.187
Iterated MILP	average	0.094	300	0.083
0% no sol	median	0.077	300	0.0000
90% zero sol gap	st. dev.	0.080	0	0.412

are solved to optimality, the basic (83%) and preprocessed MILP (79%) provide good results and clearly outperform the basic and nested branch-and-bound procedures. Also when it comes to the percentage of instances that exhibit a zero gap solution, the MILP approaches steadily outperform the branch-and-bound procedures. Note that the iterated MILP obtains a solution value that is equal to the optimal value in 90% of the instances. Although the basic MILP seems to perform better than the nested and the iterated branch-and-bound algorithms, it does not succeed to obtain at least one feasible solution in 4% of the instances. This problem, however, disappears in the preprocessed and the iterated MILP.

Due to the number of instances for which no solution could be obtained, the average solution gap of the basic MILP (2.791 %)is larger than those of the preprocessed (0.252%) and iterated MILP (0.083%), and even larger than the solution gap of the nested (1.638%) and iterated (0.557%) branch-and-bound. These latter algorithms, though, seem to be clearly outperformed by the preprocessed and the iterated MILP both in the average solution gap and the corresponding standard deviation. Especially the iterated MILP presents excellent results with respect to the both criteria. The outcome of Table 5.3 and Table 5.4 seems to confirm our proposition of Section 2.6 that commercial solvers are rapidly improving and that we should exploit their current and future capabilities, especially when we can upgrade the models with problem-specific knowledge as shown in Section 5.5.2. Since the exact MILP procedures succeed in proving the optimality of solution in many cases, their tree search can be aborted before the time limit of 300 seconds is reached. As such, they also exhibit better results in the required solution time.

5.6.4.2 Branch-and-price

Before we may proceed with the computational evaluation of the various branch-and-price algorithms in Section 5.6.4.2.3, some specific features should be examined in advance. In particular, we point our interest to the column generation optimization loop (see Section 5.6.4.2.1) and the contribution of the speed-up techniques (see Section 5.6.4.2.2).

5.6.4.2.1 Column generation evaluation

In Section 5.5.4.1.2, we proposed either a DP or an MILP approach in order to solve the pricing problems. We also indicated that there are many ways to combine the pricing problems and the RMP into a column generation optimization loop. In this section, multiple combinations are tested on their computational efficiency, though most are DP oriented. A summary of the various versions is listed below:

- DP1 and MILP: Within each iteration of the column generation optimization loop, a pricing problem is solved for each $s \in S$ in which the column with the most negative reduced cost is generated. Columns z_{st}: $RC_{st} < 0$ are added to the RMP, which is consecutively resolved.

- DP2: For a surgeon s, the column z_{st} with the most negative reduced cost is generated and added to the RMP (when $RC_{st} < 0$) which is instantly resolved. New dual prices are introduced for generating a column for a next slot.

- DP3: For a slot s, the column z_{st} with the most negative reduced cost is generated and added to the RMP (when $RC_{st} < 0$) which is instantly resolved. New dual prices are introduced for generating a new column for the same slot s. This sequence is repeated until no further columns price out. Next, columns are generated for a subsequent slot.

- DP4: A pricing problem is solved for each $s \in S$ in which a set of columns with negative reduced costs is generated. During the generation phase, only a small subset of the columns that exhibit a negative reduced cost are added to the set. The column with the most negative reduced cost, however, is always included. Next, the columns in the set are added to the RMP which is then resolved.

- DP5: A pricing problem is solved for each $s \in S$ in which a set of columns with negative reduced costs is generated. The column with the most negative reduced cost is included in this set. In contrast with DP4, a larger subset of columns with a negative reduced cost is registered. Next, the columns in the set are added to the RMP which is then resolved.

Table 5.5 shows some descriptive statistics in order to compare the approaches on their computational efficiency. In particular, interest is given to the solution time for solving the column generation optimization loop of the root node, i.e. when no branching has yet occurred.

It is clear that all DP algorithms outperform the MILP approach. Since the solution times for the MILP procedure are in general quite high, it cannot be used to build efficient branch-and-price algorithms and is hence omitted for further analysis. With respect to the DP procedures, DP1, DP4 and DP5 outperform the other algorithms. We will apply DP1 in the branch-and-price approaches of Section 5.6.4.2.3 as it results in the smallest column

Table 5.5: Comparing the time efficiency of the column generation optimization loop (seconds).

	DP1	DP2	DP3	DP4	DP5	MILP
average	0.219	0.333	0.502	0.220	0.228	12.802
Q1	0.015	0.047	0.032	0.031	0.031	0.328
median	0.078	0.125	0.141	0.079	0.078	1.852
Q3	0.234	0.375	0.469	0.235	0.266	8.016
minimum	0.000	0.000	0.000	0.000	0.000	0.031
maximum	2.859	3.594	7.046	2.281	2.610	897.516

pool. This algorithmic approach furthermore allows for an easy incorporation of the lower bound of Section 5.5.4.3.2 since it only returns for each slot the column with the most negative reduced cost.

In about 17% of the instances, solving the LP relaxation of the SCSP results in the optimal solution for the SCSP, i.e. all column variables have an integer value. These instances, however, are characterized by easy design patterns (e.g. comparable workload, frequent switches in the operating rooms and diversified weights) and are small in size ($\leq$ 40 surgeries). As mentioned in Section 5.5.4.2.1, applying column generation may substantially decrease the gap between the optimal solution and the LP relaxation of the root node when compared to a standard MILP approach. This proposition is validated for the SCSP as shown in Table 5.6 in which we compare the basic MILP (0.057), preprocessed MILP (0.044) and the column generation approach (0.028) on the average absolute gap between the LP relaxation an the optimal solution of instances of the test set. Note that the fixation of variables in the preprocessed MILP also tightens the LP relaxation compared to the basic MILP, though to a much lesser extent than the column generation approach, which also exhibits the smallest standard deviation (0.032). We

Table 5.6: Absolute gap between the LP relaxation and the optimal solution for instances of the SCSP.

	average	median	standard deviation
Basic MILP	0.057	0.046	0.051
Preprocessed MILP	0.044	0.035	0.040
Column generation	0.028	0.020	0.032

want to remark that the LP relaxation of an instance may have a negative value as α_j can be smaller than the best (integer) value of objective $j \in J$. In other words, $w_j \cdot ((\alpha_j - bestvalue_j)/(worstvalue_j - bestvalue_j))$ can be negative. The value of the LP relaxation, however, will never be smaller than $-\sum_{j \in J} w_j.(bestvalue_j/(worstvalue_j - bestvalue_j))$.

5.6.4.2.2 Speed-up techniques

In Table 5.7, the impact of an initial solution heuristic (a), the Lagrangian lower bound (b) and the elimination of columns (c) is depicted for a depth-first branch-and-price algorithm that incorporates branching scheme 1. The table shows that the initial solution heuristic triggers a significant decrease in both the solution gap and its standard deviation. When we shift the focus to the percentage of instances that are solved to optimality, two settings, namely (a)+(c) and (a)+(b)+(c), perform best. This implies that next to the introduction of the initial heuristic, also the column elimination feature seems to be beneficial. Since both settings result in the same set of instances that are solved to optimality or feature a zero gap solution, we were able to verify the impact of the lower bound on the required solution time. On average, setting (a)+(b)+(c) decreases the solution time by 9% compared to setting (a)+(c). Therefore, we integrate all speed-up techniques in the depth-first branch-and-price procedures of Section 5.6.4.2.3.

Table 5.7: Evaluation of speed-up techniques on solution quality (depth-first, branching scheme 1).

	average sol. gap (%)	st. deviation solution gap	inst. solved optimally (%)	inst. solved zero sol. gap (%)
/	1.182	2.742	43	54
(a)	0.193	0.594	47	70
(b)	1.180	2.756	44	54
(c)	1.046	2.677	48	58
(a)+(b)	0.193	0.594	47	68
(a)+(c)	0.193	0.594	51	69
(b)+(c)	1.051	2.682	48	58
(a)+(b)+(c)	0.193	0.594	51	69

When we turn our interest to the best-first procedures, the same properties hold for the use of the initial heuristic and the lower bound calculation. In Section 5.5.4.3, though, we mentioned that eliminating columns in a best-first environment may result in regenerating columns that were already discarded from the column pool. However, a limited column pool is suited for generating surgery schedules using a commercial solver. In particular, when the column pool consists of more than 450 columns, we add it to a commercial solver for maximally 25 seconds. Next, we reset the column pool, with exception of the columns that were generated while solving the root node. In other words, without losing the exact nature of the branch-and-price algorithms, column elimination enables the intertwining of the tree generation process with an easy heuristic. Moreover, the best-first nature implies that nodes from different regions of the tree are explored and increases the variety of columns in the set.

As mentioned in Section 5.5.4.3.1, we tested 36 configurations to examine the impact of the settings of the iterated MILP on the obtained solution

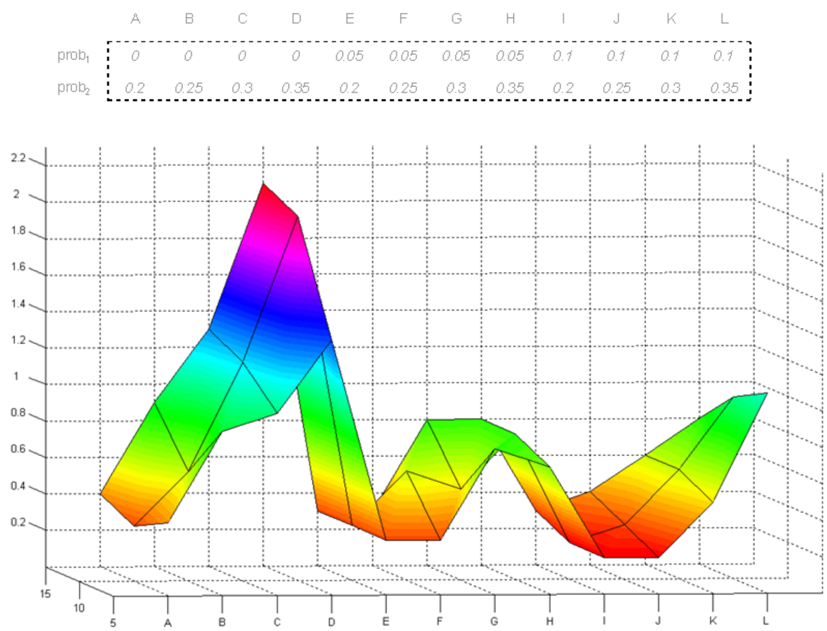

Figure 5.11: Visualizing the average solution gap in percentage that results from running the initial solution heuristic for 60 seconds for each of the 36 parameter configurations. The settings differ according to one iteration's running time (5, 10 or 15 seconds) and the values for $prob_1$ (0, 0.05 or 0.1) and $prob_2$ (0.2, 0.25, 0.3 or 0.35)

quality. The results of these tests are depicted in Figure 5.11. The figure comprises 12 combinations of the parameters $prob_1$ and $prob_2$, ranging from A to L and three running time settings, namely 5, 10 and 15 seconds for an iteration. We tested each setting for 60 seconds and expressed their solution quality in terms of the average solution gap (%). We notice that the various settings exhibit large fluctuations in the resulting gap. Setting D with a running time of 5 seconds seems to perform the worst, whereas setting I ($prob_1 = 0.1$ and $prob_2 = 0.2$) with a running time of 10 seconds per iteration performs the best. As such, this setting is chosen to tune the initial solution heuristic. Note that setting I is also the best setting for running times of 5 and 15 seconds.

Table 5.8: Computational results for the depth-first branch-and-price procedures

		absolute solution	solution time (seconds)	solution gap (%)	nr columns
Depth - Scheme 1	average	0.096	188	0.193	15826
51% opt - 0% no sol	median	0.076	251	0.000	11728
69% zero sol gap	st. dev.	0.083	115	0.594	16607
Depth - Scheme 2	average	0.096	187	0.199	20466
52% opt - 0% no sol	median	0.076	191	0.000	16451
69% zero sol gap	st. dev.	0.083	114	0.598	21367
Depth - Scheme 3	average	0.096	188	0.209	13907
51% opt - 0% no sol	median	0.078	256	0.000	6609
68% zero sol gap	st. dev.	0.083	115	0.610	16995
Depth - Scheme 4	average	0.096	191	0.189	21968
50% opt - 0% no sol	median	0.078	300	0.000	17101
71% zero sol gap	st. dev.	0.084	115	0.588	22552

5.6.4.2.3 Branch-and-price procedures

The performance of the various depth-first branch-and-price algorithms of this chapter is evaluated in Table 5.8, whereas the results of the best-first branch-and-price procedures can be found in Table 5.9.

From the tables, we see that none of the branch-and-price algorithms succeeds in proving the optimality of the solution for more than 52% of the instances. This is a rather poor result, especially when it is compared to the results of the basic and the preprocessed MILP (see Section 5.6.4.1), which indicates that the applied branching schemes may not be very restrictive and may not result in a well-balanced tree. Thus with respect to the proof of

Table 5.9: Computational results for the best-first branch-and-price procedures

		absolute solution	solution time (seconds)	solution gap (%)	nr columns
Best - Scheme 1	average	0.095	195	0.154	10156
44% opt - 0% no sol	median	0.076	300	0.000	4377
70% zero sol gap	st. dev.	0.081	115	0.505	12547
Best - Scheme 2	average	0.094	196	0.130	11116
48% opt - 0% no sol	median	0.076	300	0.000	5178
78% zero sol gap	st. dev.	0.081	115	0.447	13842
Best - Scheme 3	average	0.094	196	0.131	8382
47% opt - 0% no sol	median	0.076	300	0.000	3632
78% zero sol gap	st. dev.	0.080	116	0.467	10711
Best - Scheme 4	average	0.094	200	0.138	11896
45% opt - 0% no sol	median	0.076	300	0.000	5186
75% zero sol gap	st. dev.	0.081	115	0.456	14637

optimality, the performance should still be upgraded in the future. However, for about 68% to 78% of the instances, the branch-and-price methodology leads to a solution value that equals the optimal solution (zero solution gap), which is a steady performance. All branch-and-price procedures provide at least one feasible surgery schedule for each instance within the time limit. As mentioned, this is a valuable result when it comes to the practical implementation of the algorithms.

The smallest average solution gap (%) is encountered for the *Best - Scheme 2* algorithm and equals 0.130. Note that the best-first procedures outperform the depth-first approaches on this level. A main reason can be found in the application of the heuristic along the tree search. The results of the branch-and-price algorithms steadily outperform the exact basic MILP and the preprocessed MILP, both with respect to the solution gap and its corresponding standard deviation. This smaller standard deviation points at the fact that the branch-and-price algorithms are more stable in finding good solutions, i.e. there is less chance to obtain outlier (bad) results.

When we focus on the best performing algorithm of Section 5.6.4.1, namely the heuristic iterated MILP, an average solution gap is encountered that is only slightly better than the one of the *Best - Scheme 2* algorithm. This is remarkable as the branch-and-price procedures have to put computational effort in the proof of optimality. Note, again, that the best-first branch-and-price procedures feature a comparable standard deviation of the solution gap. We furthermore want to mention that the branch-and-price procedures, in contrast to the heuristic, provide a lower bound on the solution value and hence may provide the planner with information on potential improvements of the surgery schedule.

5.7 Problem extensions

Although the problem setting of the SCSP already seems to be quite detailed, it can easily be extended with several objectives and constraints. For instance, with respect to objective 1, one could distinguish between categories of children. In particular, the objective may be replaced by two new objectives, one addressing children below the age of 6, and one addressing the other children with a maximum age of 14. The setting of the age limits obviously depends on the opinion of the surgery planner. Also with respect to the constraints, the SCSP can be extended. For instance, in PACU 2, a further distinction is made between private and public beds. Private beds are located in isolated rooms, whereas the public beds are pooled in one area. Patients who request a private bed are not allowed to be treated in the pooled area. Regular patients, however, are allowed to be treated in a private bed, although they did not formulate a request. Expression 5.35 shows how this additional constraint can be added to the basic MILP model of Section 5.5.1. In this expression $\Theta_i^{private}$ equals 1 when the surgery of type i indicates the need for a private bed (0 otherwise). $PRIVATEcap$ denotes the capacity limit of private beds (5 private bed spaces in PACU 2). Further restrictions may also be specified for medical equipment. The X-ray, for instance, is only available from 9 a.m. on, which has its repercussions on the allowed starting times of surgeries that need this instrument. In Chapter 6, we add the extensions to the model that is used in the case study. Unfortunately, not all extensions that are interesting are that easy to incorporate and hence these require a further study in the future. We discuss some of these issues in Chapter 7.

$$\sum_{s} \sum_{i:\Theta_i^{private}=1} \sum_{p'=p-k_i-l_i-m_i+1}^{p-k_i-l_i} x_{ip's} \leq PRIVATEcap \qquad \forall p \qquad (5.35)$$

5.8 Conclusion

In this chapter, we have dealt with the analysis and optimization of an operational daily scheduling problem that is encountered in the surgical day-care center of the UZ Leuven Campus Gasthuisberg. This resulted in a problem setting, which we referred to as the SCSP, in which multiple objectives and detailed constraints are specified. We showed that the optimization of the SCSP is NP-hard and hence very difficult to solve. As such, performing algorithms were developed that were either dedicated branch-and-bound or MILP oriented. A computational testing of the algorithms turned out that, generally spoken, the MILP procedures outperform the dedicated branch-and-bound procedures. Especially the iterated MILP and the best-first branch-and-price algorithms were successful in obtaining a very small average solution gap and corresponding standard deviation. With respect to the proof of optimality, however, the branch-and-price approaches are outperformed by the basic and preprocessed MILP. The computational experiment underlined that we possess some effective algorithms to tackle the surgery sequencing problems of the test set. In the next chapter, we verify whether this result also stands when real data is introduced by means of a case study.

Chapter 6

Surgery sequencing at UZ Leuven's day-care department: A case study

Visualization leads to understanding
Understanding leads to commitment
ILOG

In 2005, Sainfort et al. [243] reported that there was only little planning at a systemic level in terms of patient flow, capacity planning or resource allocation amongst the European countries. For Flanders, in particular, they even did not find examples of current research studies dealing with the issues above. The literature review of Chapter 2 proves that this statement is currently outdated and provides already some studies on operating room planning and scheduling approaches (e.g. [16, 18]). In this dissertation, we want to add one more reference for Flanders and thus solidify the relation that should exist between theory and practice. In particular, we want to bring the algorithmic procedures of Chapter 5 to the surgical day-care center of UZ Leuven Campus Gasthuisberg and hence induce a transfer from an artificial test set, that is based on real data and probabilities, to the testing of real instances. Section 6.1 elaborates on the input data that is required to perform such a case study. When we want to adequately *solve* a problem, however, we should first be able to *see* the problem. Section 6.2 therefore introduces a graphical user interface (GUI) that not only visualizes the SCSP, but also allows the planner to interact with the algorithms which would otherwise not be accessible for practitioners. As such, planners may fully comprehend their combinatorial problem and succeed to obtain noticeable improvements. As indicated by the quotation in the beginning of this chapter, this kind of satisfaction should entail commitment, which is in our opinion a *conditio sine qua non* when it comes to both the effective implementation of academic research in practice and its sustainability in the future use. In Section 6.3 we study and evaluate the performance of the GUI and the underlying algorithms and report on the case study results that cover a two-week time period in March 2008. While researchers are definitively suited to report on the strengths and the weaknesses of the applications they develop, we should also question how practitioners think about the resulting tool as they are the real end-user. In Section 6.4, we try to incorporate their vision and evaluation of the developed application. We wrap up the major findings in Section 6.5 and provide a short conclusion.

6.1 Input data

As mentioned in Section 5.6.1, a lot of data is required to study the daily surgery sequencing problem at UZ Leuven Campus Gasthuisberg. In Section 6.1.1, we introduce the data that are necessary to reconstruct the underlying cyclic master surgery schedule. Information about the medical equipment is highlighted in Section 6.1.2, whereas the particularities of the surgery types are discussed in Section 6.1.3. Finally, Section 6.1.4 introduces information that relates to the individual patients.

6.1.1 Master surgery schedule

The master surgery schedule is defined by its constituting slots. For each slot that is created in the hospital information system, we requested multiple

Table 6.1: Extract of the data input files: the master surgery schedule

Slot ID	Discipline	Day	Slot start	Slot dur.	OR ID	Alternate
...	...	...	...	...	...	...
36	NKO	Monday	07:45	255	122	0
582	NKO	Thursday	12:50	235	122	0
53	STO	Wednesday	07:45	540	122	0
18	CON	Tuesday	07:45	540	123	0
43	ORT	Wednesday	07:45	255	123	0
41	ORT	Wednesday	12:00	285	123	0
19456	ORT	Friday	07:45	540	124	0
60	TRH	Thursday	07:45	536	124	0
14	ABD	Monday	07:45	540	125	0
3016	TRH	Thursday	12:00	285	125	0
72	VAT	Wednesday	07:45	240	125	0
3721	DER	Friday	07:45	540	126	1
316	GYN	Friday	07:45	540	126	1
...	...	...	...	...	...	...

attributes as represented in Table 6.1. Each entry in this table corresponds to one particular slot and provides a unique identification number (Slot ID), the medical discipline to whom the slot is assigned (Discipline) and the day of the week on which the surgery slot is scheduled (Day). Other information that can be retrieved from Table 6.1 is summarized as follows:

- *Slot dur*: This number (minutes) provides the reserved capacity of the slot. It allows the decision maker to verify whether a slot is overloaded with individual surgeries and allows for the identification of misused human resources (e.g. nurses), as they are not scheduled based on the current workload of a specific day, but based on the master surgery schedule.

- *OR ID*: Unique identification number of the operating room that corresponds to the slot. Each operating room identifier is related to one operating room name (e.g. X1 or Z3).

- *Alternate*: This parameter is equal to 0 if the slot is repeated every week. It is possible, however, that the slot is repeated every two weeks, which is indicated by a value equal to 1. This implies that some other slot(s) can be identified with the same operating room ID and day of the week. These slots then represent the alternating slots for odd and even weeks. In Table 6.1, slots 3721 and 316 are alternating: either operating room 126 is reserved on Friday for gynaecology, or it is reserved for dermatology, depending on the number of the week. We have to remark that not every slot is cyclic in nature. This list is updated for slots that are created for one particular surgery day and that specify deviations from the cyclic master. Such deviation is, for instance, triggered by the absence of a surgeon due to conferences or holidays.

6.1.2 Medical equipment

An extract of the data file that corresponds to the availability of medical instruments is provided in Table 6.2. In particular, the table lists for each instrument that is possibly used in the surgical day-care center a unique instrument identifier, the medical discipline that makes use of the instrument, the available capacity and the duration of the instrument's sterilization after use in a surgery (minutes). Note that some instruments do not require any sterilization, whereas others have a sterilization duration of 240 minutes.

6.1.3 Surgery type information

A lot of information that we need to formulate and solve the SCSP relates to the surgery types that have to be performed on the specific day. Table 6.3 provides an extract of the data:

Table 6.2: Extract of the data input files: instruments

Discipline	Instrument ID	Capacity	Sterilization (minutes)
...	...	...	...
ABD	rectoscopiedoos	2	240
ALG	laser CO2	1	0
ALG	torens olympus	1	0
NCH	metrix tubes	2	240
NKO	laserset I	1	240
NKO	rhinoseptoplastie	3	240
ORT	meniscus hechtingset	1	240
ORT	smart nail	1	240
RHK	plastische bak	9	240
TRH	colibri met zaag	2	240
MKA	extractietangen set 1	1	240
URO	cystoscoop 22CH	3	240
URO	fimosis	10	240
GYN	optiek 12mm	8	240
...	...	...	...

Table 6.3: Extract of the data input files: surgery type information

Surgery ID	Discipline	Duration			Description	Instruments
		OR	PACU 1	PACU 2		
...	...	...	...	...	...	...
51231	ABD	93	74	145	I: Lap cholecystectomie met peroperatieve cholangiografie	ABD - klein Doos GE ABD - lap CCE ABD - scopen 5mm ALG - torens olympus ALG - RX
6623XDI	GYN	62	80	177	I: Laparoscopische sterilisatie	GYN - torens storz GYN
86075	ONC	55	0	0	I: inplanteren Hickman-catheter 3 lumen	ONC - hickmann ALGEMEEN - RX
...	...	...	...	...	...	...

- *Surgery ID*: Each surgery type has a unique identifier. The UZ Leuven are currently developing their own, very detailed, coding to identify different surgeries. Up to now, however, the coding system is ICD-9 based and intertwined with some aspects of the future coding system. Next to the surgery ID, Table 6.3 also provides a short description of the surgery type (*Description*) in order to facilitate the recognition of the actual work content.

- *Duration OR-PACU1-PACU2*: For each entry in the table, the expected surgery duration (OR), stay in PACU 1 and stay in PACU 2 is depicted. These values are averages that are calculated using a spreadsheet that includes all surgeries that were performed in the surgical day-care center from 2004 to May 2008. However, trial runs of the GUI (see Section 6.2) indicated some major problems with the validity of the data concerning the recovery phases as the GUI indicated numerous capacity problems, while this was conflicting with the head nurse's experience. In cooperation with the center, we identified the main reason for the deviations, which is actually twofold. On the one hand, the stay in recovery is determined by the type of anesthesia that is applied to the patient, as mentioned in Section 5.1. We differentiate between general, regional and local anesthesia. Only patients with general anesthesia visit both PACU 1 and PACU 2. Local and regional anesthesia only implies a visit to PACU 2. Since the type of anesthesia does not only depend on the type of surgery that has to be performed, but also on the personal request of the patient, we should definitively take this attribute into consideration for the determination of the recovery durations. On the other hand, patients who are hospitalized (one-night stays, short-stays and fully hospitalized patients as explained in Section 6.1.4) skip the visit to PACU 2 and are transferred to their ward in the general hospital. The results of Section 6.3 incorporate both extensions based on patient-specific data (see Section 6.1.4).

- *Instruments*: Each surgery type is accompanied by a list of required medical equipment. Again, trial runs of the GUI reported on an excessive amount of instrument violations, compared to the head nurse's experience. One major reason stems from the inaccurate coding of the surgery types. It is not uncommon that different surgery types are currently listed under the same surgery ID, while they require a slightly different set of medical equipment. In the future, these inaccuracies should be eliminated through the introduction of the new UZ Leuven coding system. Moreover, the list only refers to the preferred types of instruments needed to perform the surgery type. Often, a substitute set or instrument (that does not appear on the list of required instruments) can be used to fulfil the surgeon's needs, which augments the implicit capacity of medical equipment. Therefore, we adjusted the capacity levels of instruments in dialogue with the head nurse to resemble the above situation. Note that a better approach would be to include instrument decision variables in the problem formulation and decide on the assignment of instruments to patients too. This, however, constitutes an area for future research.

6.1.4 Patient information

Finally, we need to include some patient-specific information, as depicted in Table 6.4. For each patient, we retrieve the identification number (eadnr), the specific surgery ID, the date of surgery and the slot in which the surgery has to be sequenced. Note that the model allows for comorbidity (i.e. multiple surgeries for a single patient are performed in one surgery session) so that a patient may be listed multiple times in the data file. Multiple parameters are also listed in the table to calculate the objectives and specify the constraints, such as the date of birth, the request for a private bed, the occurrence of the MRSA infection (value equal to 1), the type of anesthesia, the travel distance to the day-care center, intake information, etc. Although the center is actually a freestanding unit for ambulatory surgery (AMB and DAG), it should be clear from the intake information that capacity is also used, though rather sporadically, for inpatients (ONE-NIGHT, HOS and KVB). For ease of reference, the data also incorporate, for instance, the name of the patient or the supervisor of the surgery. Since the day-care center takes part in an academic teaching hospital, it should be noted that the supervisor does not always represent the person who actually performs

Table 6.4: Extract of the data input files: patient information

Eadnr	Name	Surgery ID	Date	Supervisor	Bed	Intake	Slot ID	Dur. OR	MRSA	Birth	...
...	...	...	...	...	...	...	...	...	...	...	...
64779931	Gilbert	8607AB	04/03/2008	x231751	Zaal	HOS	39	60	0	3/09/1953	...
88555718	Viviane	53051	04/03/2008	x295558	Prive	DAG	23339	60	1	4/07/1950	...
79796164	Julia	20491	04/03/2008	x160505	Zaal	KVB	2748	211	0	20/12/1942	...
55779573	Simon	2151	05/03/2008	xnko006	Prive	DAG	23338	60	0	26/06/1972	...
55845907	Patricia	8620	05/03/2008	rhiern0	Zaal	AMB	19985	60	0	7/12/1968	...
71906039	Pascal	9623	07/03/2008	x274624	Zaal	AMB	14	30	0	5/06/1942	...
86797397	Laura	5421XCA	07/03/2008	x212193	Zaal	ONE-NIGHT	19754	180	0	18/08/1974	...
14603986	Louis	8607BE	07/03/2008	x294461	Zaal	HOS	38	60	0	9/08/1990	...
61885497	Filip	31436D	10/03/2008	x285694	Zaal	DAG	2746	60	0	14/03/1973	...
62286958	Jan	20729	10/03/2008	x285649	Zaal	DAG	34	30	1	6/03/1951	...
70889488	Freddy	8021XACAA	10/03/2008	snijs1	Zaal	DAG	3016	60	0	11/05/1949	...
76305158	Fabienne	22632	12/03/2008	x261521	Prive	DAG	4820	55	0	22/03/1973	...
17321530	Antoine	86	12/03/2008	rhiern0	Zaal	AMB	23554	15	0	23/11/1992	...
...	...	...	...	...	...	...	...	...	...	...	...

the surgery (see Section 6.3.5). Remark that, similarly to Table 6.3, Table 6.4 also includes an estimate of the surgery duration (minutes). This estimate is provided by the surgeon and overrules the estimate determined by the average.

6.2 Graphical user interface

With the development of a graphical user interface (GUI), we hope to increase the accessibility of the algorithms and facilitate the interpretation of a surgery schedule's impact on the daily working practice in the day-care center. In particular, 4 different panes are constructed that transform data into understandable information. First, we introduce a pane that visualizes both the actual surgery schedule and its performance with respect to the set of objectives (see Section 6.2.1). Second, a pane is added to remind the user of the underlying master surgery schedule and inform him or her about the resulting slot utilization (see Section 6.2.2). Third, a summary of the surgery schedule that lists the sequence of surgeries within operating rooms and slots is provided (see Section 6.2.3). Finally, though quite important, the user may consult the resource consumption pattern that coincides with the particular surgery schedule of interest (see Section 6.2.4). In the next sections, we discuss the panes in more detail and show some of the GUI's capabilities. The application is coded using the Microsoft Foundation Classes (MFC) of MS Visual C++.NET and is linked with the ILOG CPLEX 10.2 optimization library [138].

6.2.1 Pane 1: Viewing the patient schedule

Figure 6.1 visualizes the head pane of the sequencing application. Each operating room is represented by a column in which its constituting surgeries are depicted. The size of a rectangle is proportional with the expected surgery duration, which may be verified using the surgery day's time grid at the outer left hand side of the figure. The color of the rectangle corresponds to the medical discipline it belongs to. A legend of these disciplines is added to the pane in the upper right corner. Note that each rectangle also features

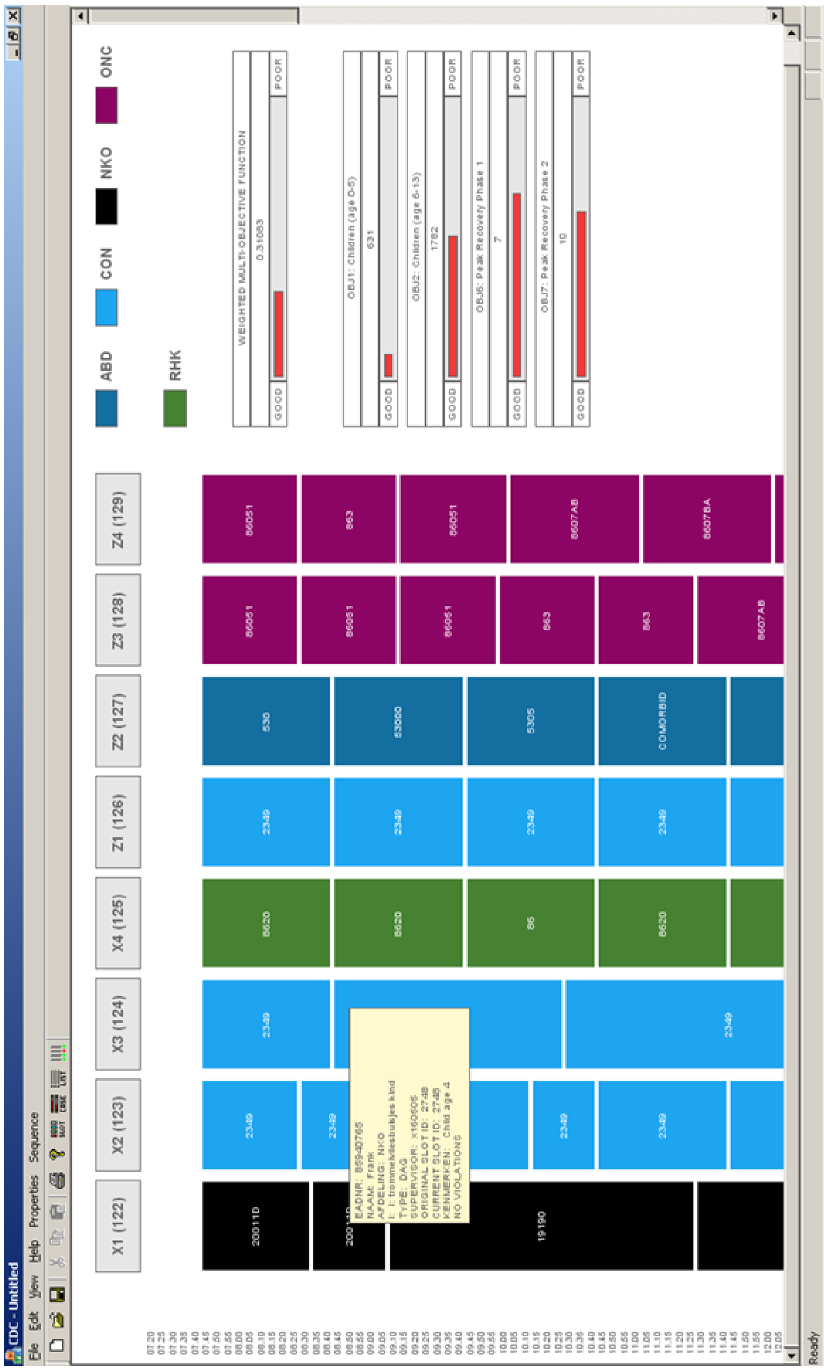

Figure 6.1: Snapshot of the surgery schedule and the resulting solution quality (pane 1)

the surgery ID of the specific patient. The color of this ID is either white or red. In contrast to a white mark, a red one indicates that the surgery violates at least one constraint that is added to the model. A quick identification of this violation, together with some patient-related information, is enabled by requesting the yellow mini-pane as shown in Figure 6.1 (right mouse click). Below the legend of the medical disciplines, the performance of the surgery schedule with respect to the objectives is visualized. Since any modification to the setting of the surgery schedule, except for changing the sequence of surgeries within a slot, may trigger changes in the extreme values of the objectives, we only evaluate the performance of the schedule as depicted in Figure 6.2 on request of the user and after the running of an optimization algorithm. We take a closer look at the objective representation in Figure 6.2.

Figure 6.2 consists of boxes and actually comprises two parts. The upper box represents the obtained value for the multi-objective function, which obviously takes the weighting of the individual objectives into account, whereas the remaining boxes each correspond to one particular objective. Note that only those boxes and thus objectives appear for which $bestvalue_j$ differs from $worstvalue_j$. Each box is accompanied by a red bar that ranges from *good* to *poor* and that visualizes the progress that still can be made with respect to that single objective. When no bar is shown, the obtained value for α_j (which is shown above the red bars, except for the multi-objective function) is equal to $bestvalue_j$. On the contrary, a bar is at its maximum length when $\alpha_j = worstvalue_j$. We want to stress that $\alpha_j = bestvalue_j$ does not imply that an excellent result for objective j is obtained. However, it means that no feasible schedule can be generated with a better performance regarding the particular objective. When for each objective $j \in J : \alpha_j = bestvalue_j$, the value of the multi-objective function is equal to 0, regardless the setting of the weights. We added in Figure 6.3 a view of the dialog in which the weights of the objectives and thus their relative importance can be changed by means of slider controls. In Figure 6.3, an equal weight is assigned to each single objective.

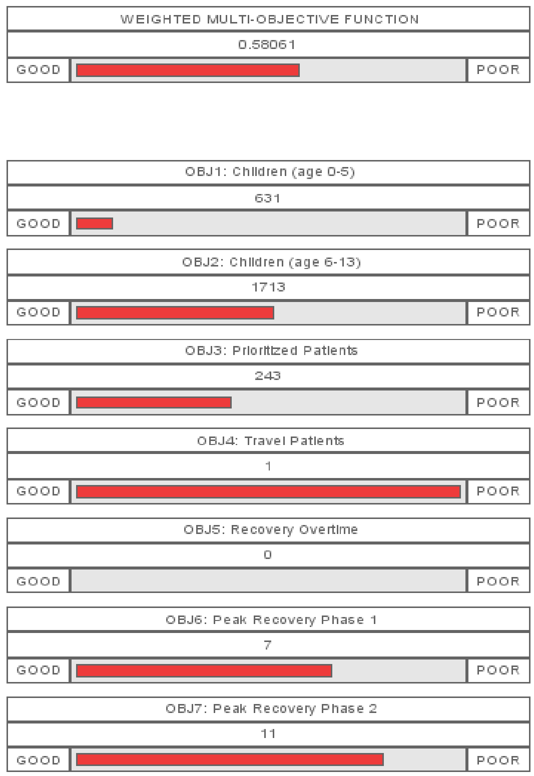

Figure 6.2: Representation of the surgery schedule's performance with respect to the comprised objectives

A double left mouse click in a particular surgery rectangle of Figure 6.1 opens the dialog that is shown in Figure 6.4. As such, the profile of the particular patient and surgery can be easily accessed and adapted by the planner when needed. In particular, adjustments can be made regarding the estimated duration of the surgery, the stay in PACU 1 (PACU2), the list of required medical instruments, a variety of patient-specific characteristics (prioritized patient, incomplete tests, MRSA, etc.) and the slot in which the surgery has to be sequenced. Changing the slot destination of a surgery occurs, for instance, when the workload of a slot steadily exceeds its capacity (see Section 6.2.2) and is also enabled by the introduction of a drag-and-drop function. This way, rectangles may be switched between operating rooms or even dragged out of the surgery schedule. For these surgeries, no slot is

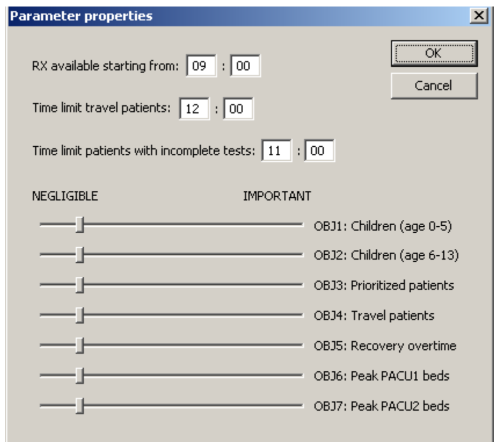

Figure 6.3: Dialog to adjust some parameter settings, such as the weights of the objectives

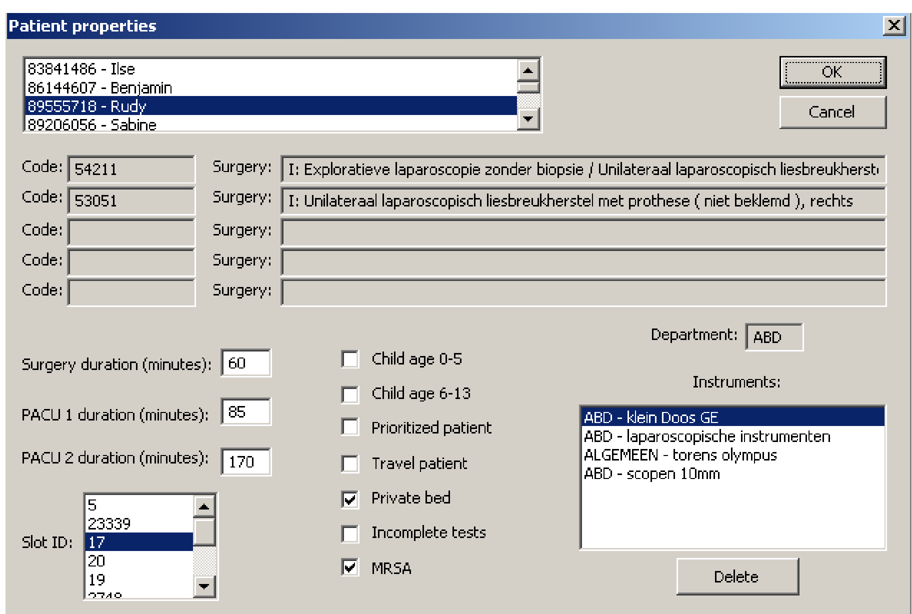

Figure 6.4: Dialog to verify and adjust patient-specific properties

Figure 6.5: Snapshot of the actual surgery schedule (pane 1) in which canceled surgeries and switches of surgeries within slots are visualized

assigned and they are excluded from the calculations, i.e. they act as canceled surgeries. The drag-and-drop function also allows to include canceled patients again and to add them to the schedule. Figure 6.5 shows a fictitious patient schedule pane in which both multiple surgeries have switched from operating room and surgeries are canceled. These latter surgeries appear on top of the screen, above the identification of the operating rooms.

6.2.2 Pane 2: Viewing the master surgery schedule

The pane in Figure 6.6 that represents the master surgery schedule is somewhat similar to pane 1 that addresses the patient schedule (see Figure 6.1). Now, however, the rectangles do not represent individual surgeries but slots of operating room capacity. The rectangles follow the color legend of pane 1, though they are not solidly colored. The current utilization of the slots is depicted on top of the screen. As mentioned, the staffing is performed based on the slots of the master surgery schedule. When there is a mismatch of workload within a specific slot, this may result in personnel overtime and

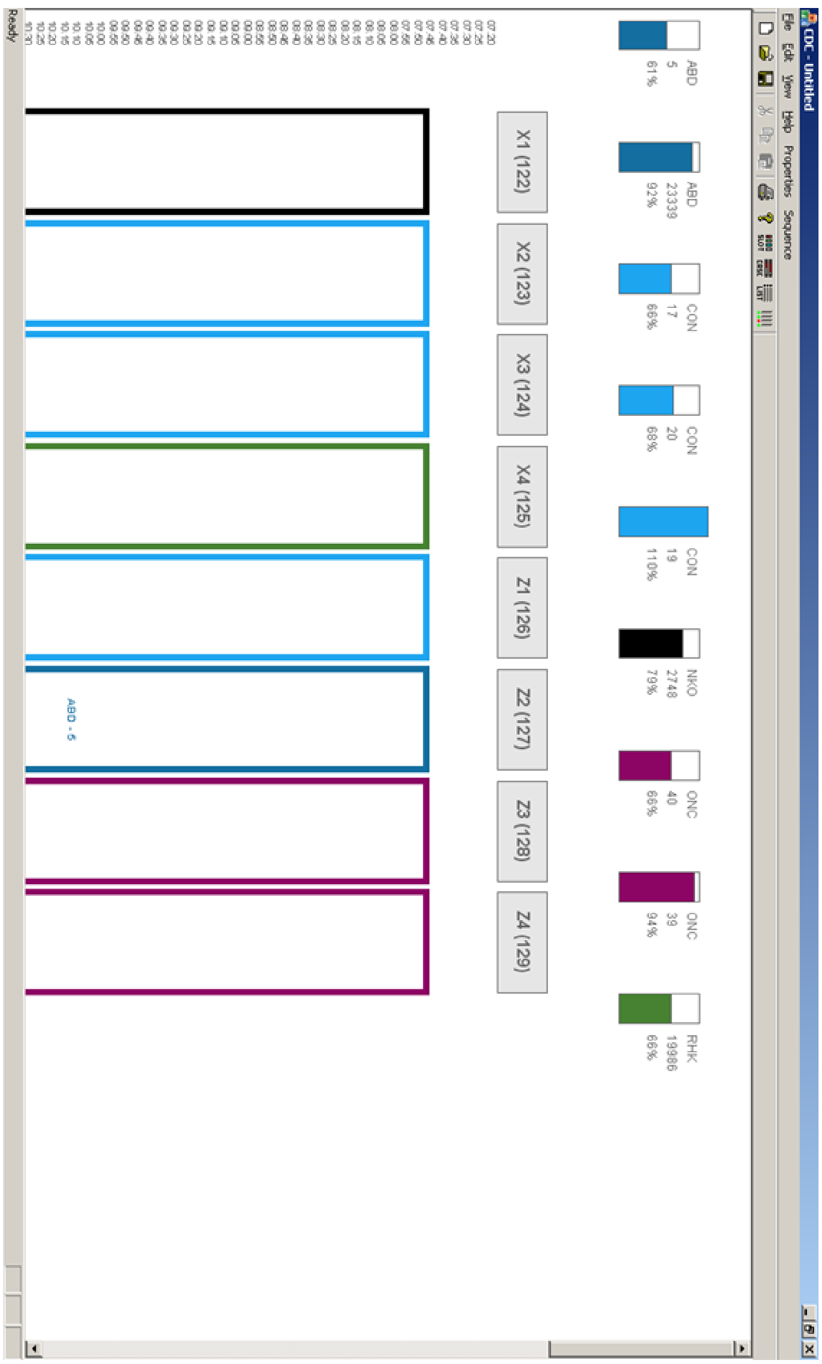

Figure 6.6: Snapshot of the master surgery schedule that underlies the actual surgery schedule (pane 2)

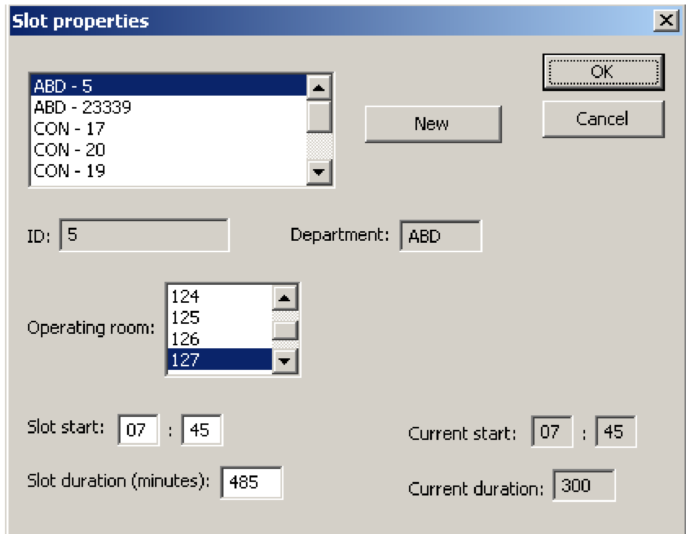

Figure 6.7: Dialog to modify the slot properties and define new slots

other inconveniences. The visualization of the slot utilization enables the planner to manually drag-and-drop surgeries to less-utilized slots when appropriate. Recall that the algorithms only sequence surgeries within each slot and thus do not decide on the assignment of surgeries to slots. This, however, constitutes an area for future research (see Chapter 7).

The starting time of a slot, as well as its duration and assigned operating room, can be easily modified by means of the dialog that is shown in Figure 6.7. Note that a modification of the starting time has its repercussion on the allowed starting times of the surgeries that are assigned to the slot. The planner is also able to introduce and define new slots and drag specific surgeries into the new capacity blocks.

6.2.3 Pane 3: Viewing the patient sequence summary

The third pane is actually the least innovative pane as it does not introduce any new information to the planner. As shown in Figure 6.8, it provides an overview of the patient sequence within each operating room and specifies,

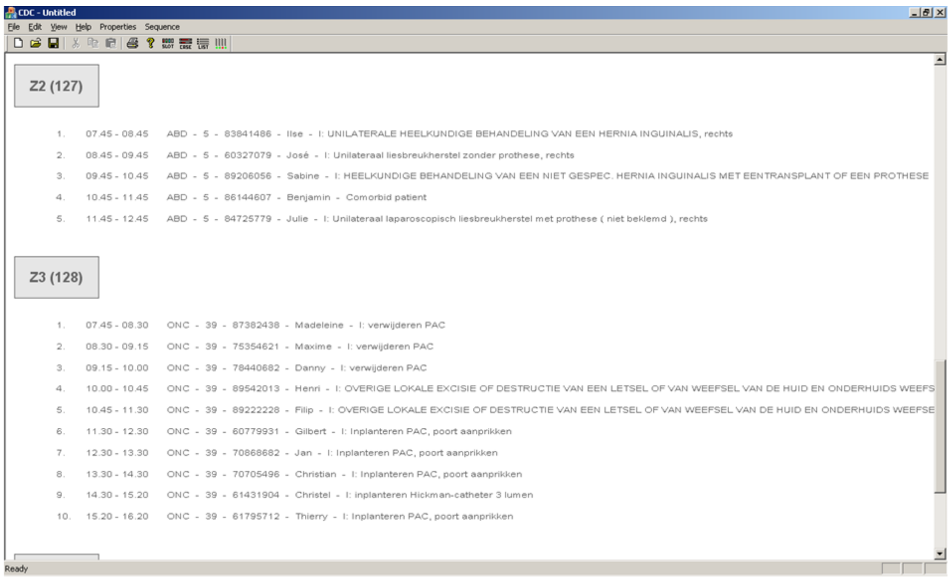

Figure 6.8: Snapshot of the patient sequence summary (pane 3)

amongst other things, the timing of the surgery, the slot ID, the patient's name and number and a description of the intervention. Patients with resource violations are depicted in red. Pane 1 (see Section 6.2.1) and Pane 4 (see Section 6.2.4) can consecutively be consulted to identify the real cause of the infeasibility. The major advantage of this summary pane is that it is conveniently outlined and hence easy to print.

6.2.4 Pane 4: Viewing the resource consumption

The fourth and final pane, which is visualized in Figure 6.9, deals with the resource consumption that coincides with the surgery schedule that is determined in pane 1. The identification of the various resources is placed at the top of the screen. Each resource is accompanied by a number that refers to the available capacity and a colored ellipse that either turns green or red. Contrary to the green color, a red ellipse points at an excessive demand for or an inaccurate use of the specific resource along the day. In order to identify the exact periods in which the conflict is to be expected, a time grid

Figure 6.9: Snapshot of the resource consumption pattern that results from the actual surgery schedule (pane 4)

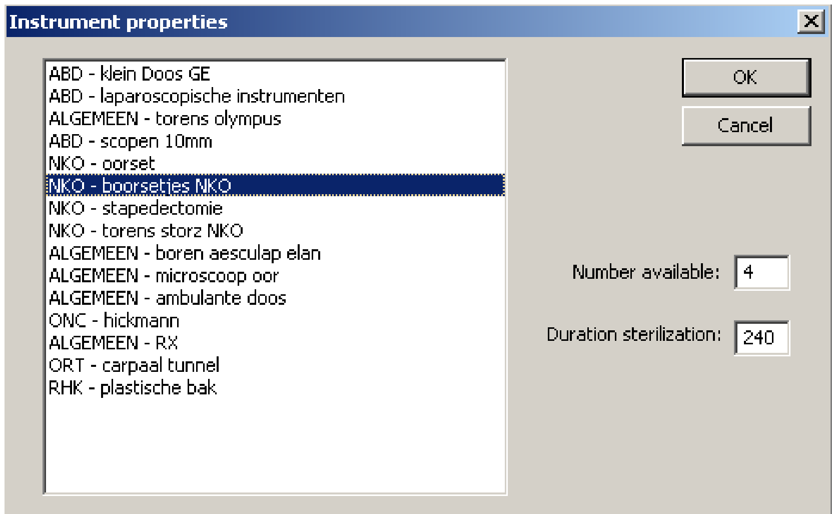

Figure 6.10: Dialog to modify the characteristics of medical equipment

is introduced at the outer left side of the pane. The intersection of a time period and the column of a specific resource provides its demand. Whenever this demand violates the supply of the resource, it turns red. Although the lists of numbers can be replaced by graphs (one for each resource) and made more visually attractive, it allows to identify any resource problems in the twinkling of an eye as much information is pooled on a small screen. The properties of the medical equipment, namely the available capacity of an instrument and its required sterilization duration after use, can be adjusted by means of the dialog in Figure 6.10. A similar dialog exists to modify the settings of the bed resources.

6.3 Case study results

We tested the GUI using data of two regular weeks in March 2008. An overview of the 10 resulting instances is shown in Table 6.5. The number of patients ranges from 44 to 64 and they are mostly spread over 8 operating rooms. Note that the number of slots is always larger than the number of

Table 6.5: Overview and feasibility characteristics of the originally sequenced surgery schedules

Date	# pat	# disc	# slots	# ORs	Infeasibleness			feasible
					instruments	beds	# pat	exists?
Monday 03/03/2008	64	8	14	8	YES	YES	9	NO
Tuesday 04/03/2008	54	5	9	8	NO	NO	0	YES
Wednesday 05/03/2008	44	8	13	8	YES	NO	2	YES
Thursday 06/03/2008	47	7	10	7	NO	YES	4	YES
Friday 07/03/2008	53	8	9	8	YES	NO	2	YES
Monday 10/03/2008	62	9	14	8	YES	YES	7	YES
Tuesday 11/03/2008	56	4	10	8	NO	YES	4	YES
Wednesday 12/03/2008	46	5	10	8	YES	YES	7	NO
Thursday 13/03/2008	55	7	10	8	YES	YES	10	YES
Friday 14/03/2008	57	7	9	8	NO	YES	2	NO

disciplines. When a lot of slots can be identified, we may expect that the number of surgeries within a slot is quite limited. When the number of disciplines is less than the number of operating rooms in use, multiple slots of the same discipline are simultaneously in progress.

Next to a description of the instances, Table 6.5 provides an evaluation of the schedule that was used on the day of surgery by the day-care center. In particular, we retrieved the sequence of surgeries in each slot from the hospital information system and checked the schedule's feasibility with respect to the bed and instrument constraints (other constraints were satisfied for each instance). In the remainder of this section, we refer to these schedules as the original schedules. Table 6.5 also indicates the number of patients that are affected by the resource conflicts, if any occur. The results of the study can be classified in three major categories. First, the original schedule is feasible. Second, the original schedule is not feasible, but a feasible schedule for the particular patient population does actually exist. Third, the original schedule is not feasible, and not even a single feasible schedule for the particular patient population can be generated. In the next subsections, we discuss these categories in more detail.

6.3.1 Feasible original schedule

Only one of the original schedules was actually feasible, namely Tuesday 4 March 2008. Since all constraints are satisfied, we are also able to evaluate the objectives and question whether the proposed sequence can be improved. Figure 6.11 compares the outcome of the original schedule with the results for the optimal schedule. The algorithmic search seems to outperform the knowledge of the human planner, as the value of the multi-objective function has decreased from 0.28306 to 0.13239. Note that the multi-objective function in this case only comprises 4 objectives. We notice a major improvement in the reduction of the peak bed use in both PACU 1 (from 6 to 4) and PACU 2 (from 9 to 6). This result is not surprising as the resulting bed occupancy is not shown in the surgery schedule itself and is hence totally not transparent to the planner. The original schedule performs similarly to the optimal schedule with respect to the remaining objectives. It should

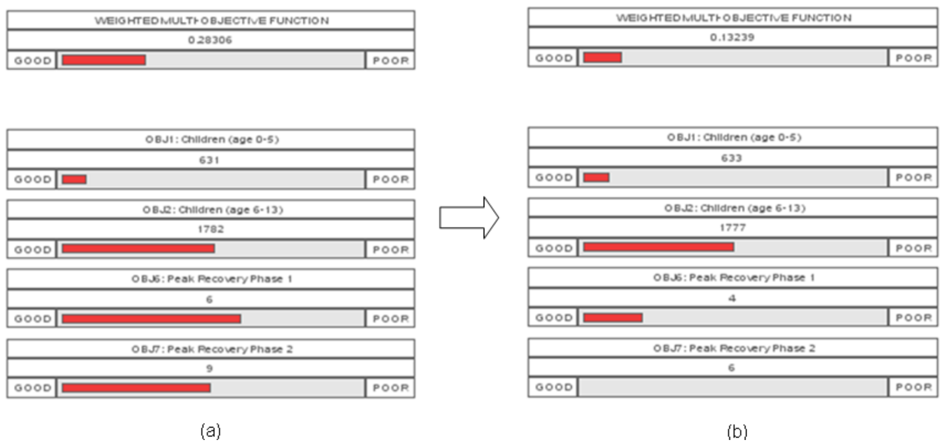

Figure 6.11: Visualizing the schedule quality on Tuesday 4 March 2008 for the original schedule (a) and the optimal schedule (b)

be noted that these objectives are much easier to capture for the human planner. We obtained the optimal schedule using the preprocessed MILP procedure in less than 2.67 seconds.

6.3.2 Infeasible original schedule - Feasible solution exists

Table 6.5 lists 6 instances for which the original schedule is infeasible, although a feasible schedule can be obtained by changing the sequence of surgeries within each slot. The extent of the constraint violations is expressed by the number of patients with at least one infeasibility. It should be noted that original schedules that suffer from both instrument and bed conflicts also exhibit the largest number of infeasible patients (up to 10 patients out of 55). No clear structure can be identified in the type of instrument or the type of bed that frequently causes the conflict during the day: violations occur for PACU 1, PACU 2 as well as the private beds, while the set of violated instruments is large and comprises instruments of all kind of disciplines. Using the GUI, we were able to identify for each instance even the optimal surgery schedule, though, the required solution time varies from 1.25 to 1921.36 seconds using the preprocessed MILP procedure. With respect to the outlier running time result we can add that a lot of time was required to provide the proof of optimality: qualitative solutions were already obtained in a matter of seconds. A solution value that equals 0 is obtained for Wednesday 5 March 2008, which implies that every single objective is realized in the best possible way. Note that in this category of instances we are unable to report on the progress in the objective function value that is achieved by the algorithmic search. The reason is that we cannot rate the original surgery schedule due to their resource infeasibility. If we relax these constraints, one should realize that the boundaries of the extreme values do not correspond anymore to the ones in the original setting, which makes a comparison deceptive.

6.3.3 Infeasible original schedule - No feasible solution exists

The final category consists of 3 instances for which no feasible solution exists. As such, the original schedule that was determined by the human planner is also infeasible. One should note that these instances do not necessarily result in a larger amount of patients with schedule violations, compared to the previous category of Section 6.3.2. The problem on Friday 14 March 2008, which only affected two patients, was that a morning slot that begins at 7.45 a.m. solely consists of patients who need an X-ray during the surgery, while this service is only provided from 9 a.m. on. These problems, however, cannot be handled by the algorithms that are developed in Chapter 5 and need structural changes such as a switch of patients to other slots or the modification of slot starting times. It should be clear that especially this category of instances is troublesome and that the GUI can assist the human planner in identifying viable solutions, i.e. making the general surgery setting feasible. The GUI reported on the non-existence of a feasible schedule in each case in less than 1 second.

6.3.4 Dealing with infeasibleness

It is interesting to know how the planner currently deals with the (expected) occurrence of violations. Today, the screening and checking of the planning is mainly directed at the unavailability of medical equipment. Two possible solutions are explored when an infeasibility is encountered. Either the head nurse tries to acquire the necessary equipment from the inpatient operating rooms in the hospital or the method of sterilization is adapted. In the latter case, the instruments are cleaned by hand instead of using machines, which decreases the required sterilization duration from 240 to 20 minutes. It should be stated, though, that the traditional cycle of sterilization is preferred when no conflicts occur. Next to the medical equipment, many problems arise with the use of the recovery bed spaces. Up to now, the planner does not adapt the surgery schedule in function of the limited available bed capacity. The instances of Table 6.5 confirmed that this frequently leads to congestion in the PACU areas. In order to avoid operating room blocking, i.e. no new patient can enter the operating room as long as the previous one is not transferred to the PACU area, patients are prematurely dismissed by the anesthetist from the recovery areas. It should be clear that this practice has a negative impact on the eventual service quality. When no solution complies, the planner may decide to cancel one or more surgeries. This decision, however, depends on many facets. The surgeries of outpatients, for instance, have priority over those of inpatients. Also surgeon-specific and patient-specific characteristics have to be taken into account. Patients who had to change their medication in preparation of the surgery, for instance, are hardly ever canceled.

6.3.5 Robustness of surgery schedules

The GUI is able to determine the optimal sequence of surgeries within each slot of the surgery schedule, based on the estimated surgery durations. We may wonder whether these sequences are still reasonable when deviations from the estimated surgery deviations occur. In other words, we question the robustness of the proposed schedules. In order to do so, we registered the sequence of surgeries that was determined by the optimal schedule of Tuesday 4 March 2008 (see Section 6.3.1) and replaced the estimated durations with the actual realized durations. At first sight, the results were promising as the realized schedule did not encounter any resource conflicts and more or less corresponded to the predicted values of the objectives. However, we noticed two major exceptions. On the one hand, the peak demand in PACU 2 increased with two more beds compared to the optimal schedule of Section

6.3.1. On the other hand, we noticed the introduction of recovery overtime as a new objective, which was definitively not a problem in the estimated schedule.

While the surgical workload of the day was estimated to 3555 minutes, its realization amounted to 4205 minutes. We wondered what the origin of the mismatch between the estimation and the realization of surgeries could be and examined two hypotheses. First, it might be possible that the surgeries inherently exhibit a significant amount of variability, although the procedures of the surgical day-care center are rather short and quite standardized (hypothesis 1). If this is the case, it seems that we cannot easily justify the deterministic scheduling approach that was developed in Chapter 5. Second, it might be possible that the durations are quite stable, but that the estimate is inaccurately set (hypothesis 2). We examined both hypotheses in detail for one particular surgery type of the discipline *CON - conserverende tandheelkunde*, namely interventions with the surgery ID = 2309 and description = *overige conserverende tandheelkunde* and included 1063 observations in the analysis. We strengthen the choice of this discipline and surgery type as the instance of Tuesday 4 March 2008 comprises 3 operating rooms for the discipline and all surgeries within the corresponding slots had a surgery ID equal to 2309. The distribution of the surgery durations is well-described by the following gamma function: $6 + GAMMA(29.4, 2.44)$ and indeed results in surgery durations that are highly volatile (hypothesis 1). However, there is one curious feature we have to report on: the estimated duration is not uniform for each patient. Also the surgeons are aware of the existing fluctuation and they seem to adapt the estimated surgery duration according to the characteristics of the specific patient. Note that this observation confirms the need for a better segmentation of surgery types and the development of a more detailed coding system, as the patient population for an intervention of type 2309 is very heterogeneous (14 different estimates for the duration of the same surgery type). As such, the impact of the stochasticity can be strongly reduced through the application of a correct segmentation. Although the concept of adapting the surgery estimates to the patient-specific properties (segment) is worthwhile, the analysis turned out that surgeons on average underestimate the surgery duration by 15 minutes. In other words, the concept of setting the estimates seems right, but the actual estimates do not seem to fit. One major cause for this underestimation stems from the role of the UZ Leuven as a teaching hospital. The time that is required to perform a surgery depends on the agent who leads the surgery: trainees require significantly more time than professors to perform the same task. On Tuesday 4 March 2008, there was one supervisor for the 3 operating rooms, which implies the presence of two trainees. Although the current hospital information system allows surgeons to specify whether a trainee will perform the surgery (and consequently automatically increase the estimated duration of the surgery), they are up to now reluctant to use the option. Maybe they are not aware of the impact of mismatching the estimated and the realized duration and hence do not fully comprehend the consequences for the entire center. As such, commitment is lacking to put an effort in using the tools and improving the estimates. Note that even within a category of agents further specification is needed. Think, for instance, of the variation in duration that stems from performing a surgery with or without teaching the students. Based on the above discussion, we believe that hypothesis 2 constitutes the main cause of the current mismatch, which is a cause the hospital management should be able to deal with in the near future when the new coding system will be fully introduced.

6.4 End-user evaluation

In the introduction of this chapter, we already mentioned that we value the opinion of the end-user in the evaluation of the research project. Below, we state the opinion of two practitioners of the UZ Leuven who were related to the project in the past few years. The goal of the exercise in this section is not to provide a *good news show* and solely highlight the strengths. Although it is important to identify the main contributions of the project for the UZ Leuven, we should be more interested in the shortcomings that currently delay the actual implementation of the research in the short term.

The application that was developed to optimize the daily surgery scheduling *problem at the surgical day-care center and that includes the objectives and constraints we agreed upon, gives us a lot of opportunities. Now we are already able to have an overview of the organizational problems we may expect one day in advance. Using the tool, various alternatives can be tested and evaluated. This makes it a valuable instrument for us on day -1, i.e. the day before surgery and may lead to a significant time gain for the local heads of the center. We especially appreciate its user-friendliness and the visual representation of the planning issues as it facilitates the discussion of problems and alternatives. Moreover, it provides a means to direct the purchase of equipment, as mismatches now can be identified in an objective manner, and to justify the resulting investments. However, we still see some shortcomings in the current use and hence opportunities that should be exploited in the future:*

- *The estimated surgery duration is not allowed to significantly deviate from the real realization. Although for some disciplines the current estimations work well, other disciplines feature large fluctuations.*
- *The coding of the surgery types should be extended. Only then, an infallible linking with the required medical equipment and an improvement in the duration estimates can be achieved.*
- *The linking with the electronic patient file that is centrally managed in the hospital is a prerequisite to apply the tool in practice, as it enables a fully automatic inclusion of data into the model and registration afterwards.*
- *Perhaps one should add some kind of undefined objective that can be used for uncommon or exceptional features.*

- *In the future, we would like to include PACU 3 in the analysis. We believe that one can technically deal with this extension as it resembles the inclusion of PACU 1 and PACU 2. However, before we can do so, attention should be paid to a better time registration of the transition between PACU 2 and PACU 3.*

It is currently unclear to us how the application can be used as an online instrument, i.e. on the day of surgery. This, however, would be very helpful to anticipate the absence or failures of medical instruments or the impact of uncertainty in the surgery durations. Although we are not able to drastically change the surgery schedule at that time (recall that patients arrive approximately only one hour in advance of their original surgery starting time), an updated view on the upcoming resource use may induce some organizational improvements.

In short, we enjoyed the cooperation with the Faculty of Business and Economics and appreciate the awareness and the added value that stems from the many dynamic conversations and meetings. We believe multidisciplinary research is favorable for all parties involved. In the future, this cooperation will gain in importance due to an apparent shortage in medical and paramedical staff.

Pierre Luysmans - Stafmedewerker operationeel beleid operatiekwartieren
Annegret Van Gool - Adjunct-hoofdverpleegkundige E596 CDC

It seems that the planner realizes the current surgery estimation problem and the inaccuracy of the coding system, as explained in Section 6.3.4. These remarks, however, are directed to the hospital management and should be solved on their initiative and using their experience.

The practitioners also report on a missing link between the application and the electronic patient files that are available in the hospital information system. Although we acknowledge the importance of this linking aspect, we

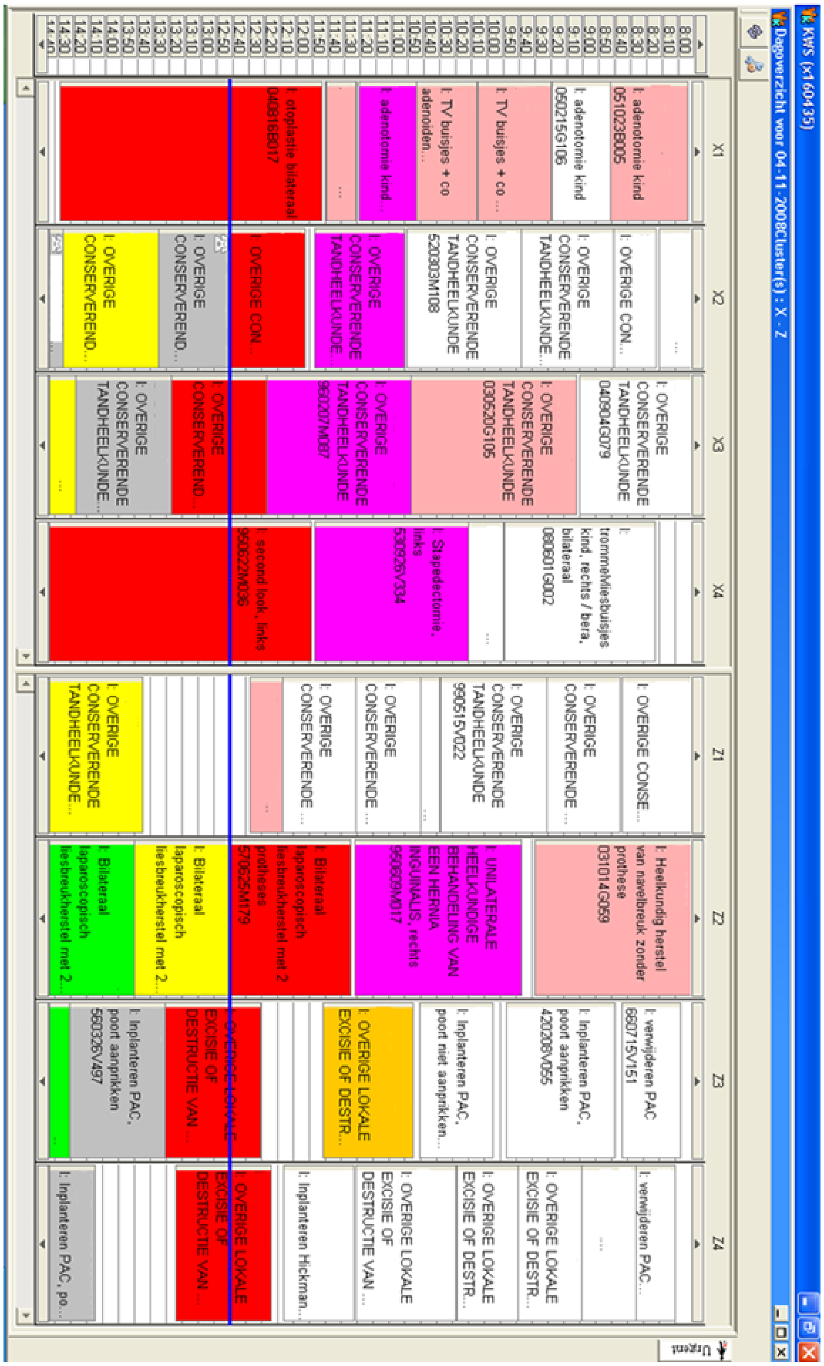

Figure 6.12: Snapshot of the patient tracking system in the surgical day-care center of the UZ Leuven Campus Gasthuisberg

believe that also this issue has to be solved by the hospital, and not by the researcher, for the following reason. The UZ Leuven has a strategic policy to develop the required information systems in-house using their own informatics department. We encourage this policy, as it secures the future sustainability of the developed applications, which is undoubtedly very important. Unfortunately, the waiting list of projects that have to be handled by the informatics department is huge. Our project has the disadvantage that no direct financial gains (expressed in yearly savings) are visible when the tool would be implemented. As such, it is hard to improve the priority of the project. However, our project also has a major advantage for the informatics department that definitively should be exploited in the negotiations. The surgical day-care center already applies a visualization tool that depicts the progress of the surgeries along the day. A snapshot of this application is provided in Figure 6.12. Using color codes, each stakeholder in the center can verify the stage in which a particular patient is. This may vary, for instance, from *not yet arrived* to *ready for surgery* or *ongoing surgery*. The similarities with pane 1 of the GUI (see Figure 6.1) cannot be missed. Since the tracking system is already connected to the electronic patient file, it is perfectly manageable to provide all the input that is required to apply the algorithms and show the resource consumption based on the resulting schedule as done in the GUI. We can even go one (important) step further, and monitor the quality of the surgery schedule online on the day of surgery as the rectangles that represent the surgeries are automatically adjusted to the realized durations. We can see in Figure 6.12 that the snapshot was created at 0.40 p.m.: all surgeries that are displayed above the line are already finished (size of the rectangle is the realized duration), whereas those below the line still have to be performed (size of the rectangle is the planned duration). Surgeries that cross the line are actually in progress. This ability to update the durations significantly improves the accuracy of the predictions that can be made for the future use of resources and potential resource conflicts. When needed, the sequences of surgeries that still are to be performed can be re-optimized under certain conditions, as remarked by the practitioners. The GUI that is developed in this chapter should assist the planner to convince the hospital management of both its managerial importance and the existing relationship with the tracking tool. Once again, this should increase the hospital management's understanding of the importance to have an optimized surgery planning and improve the commitment and the desire to invest in its actual implementation.

Finally, the practitioners state a remark on the inclusion of a generic objective and extension of the application to PACU 3. We were very pleased to see that they personally stated that these extensions probably will not be a major problem as there are many similarities to features that are already incorporated in the model. This clearly points at their understanding of both the problem and the way in which the model deals with the problem. Indeed, both extensions can be efficiently added to the models in a future phase.

6.5 Conclusions

In this chapter, we examined whether the models and insights that were developed in Chapter 5 can effectively be applied in practice. We developed a graphical user interface to facilitate both the interaction with the setting of the models and the interpretation of the results. We reported on the important data gathering phase and presented case study results for 10 surgery days at the surgical day-care center of the UZ Leuven Campus Gasthuisberg. By means of the application and thus adapting the sequence of surgeries within the slots, we were able to strongly improve the surgery schedule quality compared to the original schedules. If no feasible schedule could be obtained, the GUI proved to be a valuable instrument in the evaluation of structural changes such as a new assignment of surgeries to slots or a modification of slot starting times. Although the case study results are promising, the actual implementation of the application seems difficult. We highlighted some major reasons for this observation and provided some suggestions to improve both the implementation speed and the accuracy of the predicted resource consumption pattern. The key to these improvements, however, lies with the hospital management.

Chapter 7

Conclusion and future research

We conclude the dissertation with this chapter and summarize the content that was captured in its constituting parts. Throughout the discussion, we point at some main contributions and provide directions for future research.

In **Chapter 1**, we pointed at the importance of health care services in today's society and stressed the central role of hospitals and their operating theater. Since these facilities are recognized to be major cost drivers of health expenditure, they provide an interesting setting for research projects. Especially the study of outpatient or ambulatory settings opens perspectives as they currently gain in importance. The increase in demand necessitates an efficient use of scarce and costly resources and hence constitutes a motivation to study the planning and scheduling aspect from an operations management view.

We screened the literature on operating room planning and scheduling in **Chapter 2** and comprehensively structured the set of retained manuscripts, i.e. manuscripts that appeared in or after 2000. The structure of the chapter is also the main contribution of the review as it studies the literature from various perspectives, which we referred to as descriptive fields. In particular, 7 fields were identified that encompass the patient classes, the performance criteria, the decision delineation, the type of analysis, the solution or evaluation technique, the explicit incorporation of uncertainty and the applicability of the research. Especially the delineation of the decision is new and provides valuable information to the reader, as it is far more detailed than the traditional view that is based on a strategic, tactical and operational perspective. Using the descriptive fields, accompanied by the detailed tables in each section of the literature review, researchers now should be able to easily identify manuscripts with significant relationships to their research and to reconstruct the content of manuscripts by cross-referencing over the multiple fields. Throughout the review, two main directions for future research could be identified. On the one hand, research should explicitly incorporate uncertainty, both with respect to the individual processes and the systems, and widen the scope to the inclusion of non-elective surgery management. On the other hand, research should strive towards the study of integrated operating theaters and explicitly link the surgery planning and scheduling decisions with the upstream and downstream processes. Achieving both goals, however, results in problem settings that are extremely complex and that are hence mostly simplified in order to be solved. This, however, brings us to an important question researchers should dare to ask: "Should we examine realistic and thus complex problem settings and try to improve the current practice as much as possible, or should we examine a simplified and tailored version of the problem and solve it to optimality?" In our opinion, the largest societal contribution stems from the first approach, although many researchers will disagree. However, this setting implies that information from multiple disciplines is required to fully comprehend the problem. With respect to hospitals, this may include informatics, medical know-how, legislation and economics. The conduct of benchmark studies and studies that address the problems that coincide with the implementation of research in practice, i.e. studies that are currently lacking in the literature, should contribute to the current state of field expertise and improve the state of multidisciplinary research, which also embeds the research on operating room planning and scheduling.

The literature review also revealed that the domain of operating room planning and scheduling lacks clear definitions. Think, for instance, of the misuse of overutilization and overtime as mentioned in Section 2.3. This observation does not only apply to concepts, but also to the definition of the problem setting that is dealt with in the manuscripts. Think, for instance, of the multiple interpretations researchers give to a master surgery schedule (see Section 2.4). In order to clarify and to structure the content of forthcoming research on operating room planning and scheduling, we proposed in **Chapter 3** a classification scheme that leans on a reduced number of descriptive fields that were discussed in the literature review. In particular, the scheme embeds information on the patient characteristics (α), on the type and the subject of the decision that needs to be addressed in the problem and the according degree of operating room integration (β), on the explicit incorporation of uncertainty (γ) and on the particular set of performance criteria (δ). The classification scheme balances notation with information and strives for clarity, brevity, flexibility and unambiguity. Even if researchers disagree with the current trade-off of these features in the classification scheme, we hope that it may already lead them to consider some important problem characteristics while writing down their problem description. In the near future, we hope to finalize and to validate the classification scheme by incorporating the opinions of an extended set of experts in the domain of operating room planning and scheduling.

While Chapter 2 provides the readers with an updated view on the academic state-of-the-art concerning operating room planning and scheduling issues, **Chapter 4** directs the attention to the practitioners in Flanders. In particular, two goals were addressed. On the one hand, we wanted to identify the state of the hospital's planning and scheduling policies and gather general information on their operating theater setting. On the other hand, we wanted to identify to what extent academic research has an impact on their current practice and hence study whether hospitals easily adopt the suggestions or insights that are provided by the researchers. The survey results, which are based on a satisfying response rate, indicated that the level of academic knowledge is much more advanced than the knowledge that is currently applied to the hospitals. In our opinion, this gap may be decreased in two ways. On the one hand, researchers should relate their research to practice in a much more detailed manner. On the other hand, practitioners possibly lack insights in the contribution that can be obtained by the application of operations management and operations research techniques to their domain, so that it is necessary to create awareness of the current capabilities. Although the general trend of the results in the chapter is clear, we should warn the reader about the possible bias that coincides with the conduct of a survey. Therefore, future interviews seem the obvious means to confront the respondents with their answers and validate the results in detail.

Chapter 5 addressed a surgical case sequencing problem that originated at the UZ Leuven Campus Gasthuisberg. The question was to determine the starting times of surgeries within each slot of the underlying master surgery schedule so that children and prioritized patients are scheduled as early as possible, travel patients are scheduled from a certain reference period on, recovery overtime is minimized and the peak use of beds in PACU 1 and PACU 2 is minimized. Setting the surgery starting times, though, is subject to a detailed set of constraints that includes, amongst other, the use of medical equipment and the corresponding sterilization, the limited bed capacity or the occurrence of MRSA infections. Multiple solution procedures, which were either dedicated branch-and-bound or MILP oriented, were developed and thoroughly tested with respect to their computational requirements and the obtained solution quality. Especially the MILP procedures proved their contribution in solving the problem and provided satisfying results.

Many ideas for future research can be related to the research setting that was dealt with in Chapter 5.

- We briefly mentioned in Section 5.1 that the procedure to schedule surgeries actually consists of two steps, namely an assignment step and a sequencing step. Although we restricted the focus in this dissertation to the sequencing step, the importance of the assignment step cannot be neglected. It should be clear that the way in which the population for a specific surgery day is determined, has a major impact on the improvements that still can be achieved in the sequencing step. Various assignment policies can be developed and evaluated on their performance. As such, the occurrence of resource conflicts can be drastically reduced. Since we do not know which patients will require surgery in the future, the assignment policies should be developed in an on-line environment.

- The sequencing problem may be extended to incorporate decisions on the required medical equipment. We mentioned in Section 6.1.3 that actually multiple types of instruments can be used to execute a specific action: e.g. we can use *either* laser set I *or* laser set II. In other words, the instruments have some (yet not all) capabilities in common. One way to incorporate this type of constraint in the model is to add a supplementary decision variable that assigns instruments to surgeries.

- When multiple slots of the same discipline are scheduled on the same surgery day, we should allow surgeries to be switched between the slots. The GUI that was introduced in Chapter 6 only allowed for manual switches induced by the human planner. However, it is possible to extend the algorithms to choose on the assignment of surgeries to slots within the scope of one specific surgery day. We expect that this extension will make the resulting problem much harder to solve. Moreover, a new type of constraint that states that one specific surgeon cannot act in more than one operating room at the time, possibly has to be added to the formulation. Note that the extension may also lead to the introduction of a new objective in which the slot overload, which currently also has to be manually adapted, can be minimized.

- One may question whether the solution procedures can easily be applied to some other setting than the one of the UZ Leuven Campus Gasthuisberg. As long as the focus is restricted to an outpatient setting, this definitively should be possible without major effort. However, the transition gets troublesome when a switch has to be made to an inpatient setting. Although some extensions would be very easy to include, such as the inclusion of the ICU, a problem is identified in the increased variability of the surgery durations and hence in the preciseness of the schedule outcome. Therefore, we should work towards an efficient stochastic version of the procedures and include important particularities of inpatient scheduling, such as the changeover times between surgeries.

- Obviously, we should also consider the extensions that are requested by the practitioners in Section 6.4 and elaborate on the performance of the algorithms by introducing, for instance, new branching schemes or bounding characteristics or changing the parameter settings.

In **Chapter 6**, we applied the procedures that were developed in Chapter 5 to 10 real instances that were encountered at the surgical day-care center of the UZ Leuven Campus Gasthuisberg. By means of the case study results, we were able to highlight the algorithm's effectiveness as 7 out of 10 problems were solved to optimality, whereas the current hospital practice only featured one feasible schedule. The interpretation of the results and the accessibility of the algorithms were clearly enhanced by the introduction of a graphical user interface. This visualization tool contributes to the understanding of the optimization problem and hence can act both as an operational instrument in the daily scheduling practice and a strategic instrument in discussions. The most important discussion probably concerns the implementation of the research that was conducted in the main chapters of this dissertation. We hope that the findings of this dissertation may facilitate the understanding of the importance of the topic, and create the commitment that is necessary to transform ideas into results.

Appendix A

In this Appendix we derive Expression (5.30 or A-8) from Expression (5.1 or A-1). In Expression (A-2), we separate a constant term that is neglected during optimization from the term that needs optimization. In Expression (A-3), we furthermore distinguish between the objectives that are entirely determined within a column ($j \in J : j \leq 4$) and those that only can be determined by aggregating the columns into a surgery schedule ($j \in J : j \geq 5$), as explained in Section 5.5.4.1.1.

$$\sum_{j \in J} w_j \cdot \left(\frac{\alpha_j - bestvalue_j}{worstvalue_j - bestvalue_j} \right) \tag{A-1}$$

$$= \sum_{j \in J} \frac{w_j \cdot \alpha_j}{worstvalue_j - bestvalue_j} - \sum_{j \in J} \frac{w_j \cdot bestvalue_j}{worstvalue_j - bestvalue_j} \tag{A-2}$$

$$= \sum_{j \in J : j \leq 4} \frac{w_j \cdot \alpha_j}{worstval_j - bestval_j} + \sum_{j \in J : j \geq 5} \frac{w_j \cdot \alpha_j}{worstval_j - bestval_j} - \sum_{j \in J} \frac{w_j \cdot bestval_j}{worstval_j - bestval_j} \tag{A-3}$$

With respect to the first term in Expression (A-3), we still have to eliminate the use of the auxiliary variables α_j and introduce the binary decision variables z_{st} together with their corresponding cost parameter c_{st} (Expression A-4 to A-7).

$$\sum_{j \in J: j \leq 4} \frac{w_j \cdot \alpha_j}{worstvalue_j - bestvalue_j} = \sum_{j \in J: j \leq 4} \frac{w_j \cdot \sum_{s \in S} \sum_{t \in T_s} c_{st}^j \cdot z_{st}}{worstvalue_j - bestvalue_j} \tag{A-4}$$

$$= \sum_{s \in S} \sum_{t \in T_s} \left(\sum_{j \in J: j \leq 4} \frac{w_j \cdot c_{st}^j \cdot z_{st}}{worstvalue_j - bestvalue_j} \right) \tag{A-5}$$

$$= \sum_{s \in S} \sum_{t \in T_s} \left(\sum_{j \in J: j \leq 4} \frac{w_j \cdot c_{st}^j}{worstvalue_j - bestvalue_j} \right) \cdot z_{st} \tag{A-6}$$

$$= \sum_{s \in S} \sum_{t \in T_s} c_{st} \cdot z_{st} \tag{A-7}$$

Since for each objective $j \in J : j \leq 4$, the cost of the total surgery schedule is equal to the sum of the costs of the individual columns that constitute the surgery schedule, we have that $\alpha_j = \sum_{s \in S} \sum_{t \in T_s} c_{st}^j \cdot z_{st}$ (Expression A-4). As shown by the transition from Expression (A-6) to (A-7), we have that $c_{st} = \sum_{j \in J: j \leq 4} \frac{w_j \cdot c_{st}^j}{worstvalue_j - bestvalue_j}$. Finally, incorporating Expression (A-7) into Expression (A-3) leads to the objective function of the RMP as described in Section 5.5.4.1.1 (Expression A-8).

$$\sum_{s \in S} \sum_{t \in T_s} c_{st} \cdot z_{st} + \sum_{j \in J: j \geq 5} \frac{w_j \cdot \alpha_j}{worstvalue_j - bestvalue_j} - \sum_{j \in J} \frac{w_j \cdot bestvalue_j}{worstvalue_j - bestvalue_j} \tag{A-8}$$

Appendix B

In this Appendix we elaborate on the dynamic pricing problem introduced in Section 5.5.4.1.3 in order to handle the occurrence of infections. The modified recursive dynamic programming formulation is stated by Expressions (A-9) and (A-10). In these expressions, $\Phi(h,q)$ represents a value to determine the feasibility of adding sequence q to state h and $\Psi(h,q)$ indicates the stage that is reached after adding sequence q to state h. $\beta_g(h)$ equals 1 if an infected patient is introduced at stage g (0 otherwise).

$$RC_s^{*} = \min_{h \in H_1} \left\{ \min_{q \in Q_{\beta_1(h)} : \Phi(h,q) \neq 0} \left\{ C(h^{\emptyset}, q^{\emptyset}, h, q) + F_{\Psi(h,q)}(h,q) \right\} \right\} - \lambda_s \tag{A-9}$$

$$F_{\Psi(h,q)}(h,q) = \min_{\substack{h' \in H_{\Psi(h,q)+1} : \\ (h \cup q) \subset h'}} \left\{ \min_{\substack{q' \in Q_{\beta_{\Psi(h,q)+1}(h')} : \\ \Phi(h',q') \neq 0}} \left\{ C(h,q,h',q') + F_{\Psi(h',q')}(h',q') \right\} \right\} \tag{A-10}$$

When the transition from state h at stage g to state h' at stage $g+1$ coincides with the decision to schedule the surgery of an infected, we try to add an eligible and sequenced set of surgeries $q \in Q_1$ to the schedule so that the supplementary restrictions introduced by the infection cannot influence future decisions anymore. However, when such a transition denotes the scheduling of a regular patient (i.e. a patient without the MRSA infection), we apply the logic of the original DP formulation of Equations 5.32 and 5.33. It will become clear that this is actually equivalent with the addition of the only sequenced set in Q_0, namely $q^{\emptyset}$. Note that, due to the addition of the sequenced sets, decisions possibly will not have to be made in every stage now.

Before we can initiate the recursive function, some calculations need to be done. First, we will try to aggregate idle periods into a cleaning type since this would reduce the number of surgeries to be scheduled (see Section 5.5.2.2). Second, we have to enumerate the sequenced sets of surgeries $q \in Q_1$. Except for $q^{\emptyset} \in Q_1$, each sequenced set q consists of a combination of idle periods, infected surgery types and cleaning types. Although we do not discuss the enumeration algorithm in detail, it is important to know that these sequenced sets either end on an infected surgery type or on a cleaning type. Formulating the DP using the sequenced sets implies that the occurrence of infections is mainly handled by choosing eligible paths through the stages, instead of assigning costs for infeasibleness.

When state h is realized by scheduling a infected surgery type, we have to determine whether the choice of a sequenced set q after realization of state h would lead to a feasible path ($\Phi(h,q) \neq 0$). When state h is realized by scheduling a regular patient, i.e. a patient without the MRSA infection, we add the empty sequenced set $q^{\emptyset}$, set $\Phi(h,q) = 0$ and take the next decision at stage $\Psi(h,q) + 1 = |h| + 1$. In order to determine the feasibility of a sequenced set, a set of conditions has to be checked. It is not allowed to schedule a sequenced set q when this would lead to a schedule in which more patients of a certain surgery type are scheduled than represented in the patient population of the surgeon ($\Phi(h,q) = 0$). Three situations may neutralize the effects that stem from the MRSA infection, i.e. ensuring that any type of surgery can be initiated after the addition of the sequenced set. First, it is possible that no more surgeries have to be scheduled or that the remaining surgery types, i.e. those that still have to be scheduled, only consist of idle types ($\Phi(h,q) \neq 0$ and $\Psi(h,q) = |h| + |q|$). This implies that we could reach the ending time of the specific slot. Second, it might be possible that the sequenced set q ends on a cleaning type ($\Phi(h,q) \neq 0$ and $\Psi(h,q) = |h| + |q|$). Finally, we allow the consequences of the infection to be fully neutralized by idle periods, though now without reaching the end of the session ($\Phi(h, q) \neq 0$ and $\Psi(h, q) = |h| + |q| + k_{clean}$). When none of the above situations apply, the sequenced set q cannot be added to the surgery schedule and a next sequenced set should be consulted ($\Phi(h, q) = 0$).

The cost function $C(h, q, h', q')$ is constructed in a similar way as in the original DP formulation of Section 5.5.4.1.3, except that we possibly have to incorporate objective costs, duality costs and infeasibility costs of multiple surgeries. The number of surgeries introduced to the schedule during a stage transition is equal to $\Psi(h', q')$-$\Psi(h, q)$. Since q' is sequenced, we can easily associate a starting time with each surgery. With respect to the infeasibility costs, we want to stress that $C(h, q, h', q')$ could be equal to ∞ not only due to pre-surgical tests, but also due to infections when the additional cleaning of the operating room affects the surgical block of the subsequent slot, given that there is a slot switch in the operating room.

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