KATHOLIEKE UNIVERSITEIT
LEUVEN

Faculty of Business and Economics

A decision support system for surgery sequencing at UZ Leuven's day-care department

Brecht Cardoen and Erik Demeulemeester

DEPARTMENT OF DECISION SCIENCES AND INFORMATION MANAGEMENT (KBI)

KBI 1106

A decision support system for surgery sequencing at UZ Leuven's day-care department

Brecht Cardoen†‡*, Erik Demeulemeester ‡

†Vlerick Leuven Gent Management School, Operations and Technology Management Center, Reep 1, B-9000 Gent, Belgium, brecht.cardoen@vlerick.be

‡Katholieke Universiteit Leuven, Faculty of Business and Economics, Department of Decision Sciences and Information Management, Naamsestraat 69, B-3000 Leuven, Belgium, brecht.cardoen@econ.kuleuven.be, erik.demeulemeester@econ.kuleuven.be

Abstract

In this paper, we test the applicability of a decision support system (DSS) that is developed to optimize the sequence of surgeries in the day-care center of the UZ Leuven Campus Gasthuisberg (Belgium). We introduce a multi-objective function in which children and prioritized patients are scheduled as early as possible on the day of surgery, recovery overtime is minimized and recovery workload is leveled throughout the day. This combinatorial optimization problem is solved by applying a pre-processed mixed integer linear programming model. We report on a 10-day case study to illustrate the performance of the DSS. In particular, we compare the schedules provided by the hospital with those that are suggested by the DSS. The results indicate that the DSS leads to both an increased probability of obtaining feasible schedules and an improved quality of the schedules in terms of the objective function value. We further highlight some of the major advantages of the application, such as its visualization and algorithmic performance, but also report on the difficulties that were encountered during the study and the shortcomings that currently delay its implementation in practice, as this information may contribute to the success rate of future software applications in hospitals.

Keywords: Decision support system, optimization, visualization, health care application

1 INTRODUCTION

Many reasons can be found to stress the importance of an adequate planning and scheduling of surgeries. The ageing population and its resulting increase in the demand for health care services puts a continuous pressure on scarce and costly resources, such as the nursing personnel

*Corresponding author

[8]. However, hospitals are not only confronted with an increase in the demand for surgery, they have also experienced a shift from inpatient surgery to ambulatory surgery or outpatient surgery, i.e. patients who are admitted and discharged from the hospital on the same working day [15]. Procedures that were previously performed in an inpatient setting, are now performed as day surgery because of the progress in surgical expertise and the introduction of new anaesthetic and analgesic medications. The International Association for Ambulatory Surgery [11] forecasts that at least 75%, if not more, of all procedures will ultimately be carried out in an ambulatory setting.

Outpatient surgery exhibits particular advantages over inpatient surgery for patients, hospitals and health care funders [12]. Patients spend less time in the hospital, recover in their own home and 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 since they are separated from sicker patients. In short, day surgery leads to an increased patient satisfaction. Furthermore, as procedures are typically shorter and standardized, uncertainty is reduced and thus hospitals can manage their schedule more efficiently. This reduced uncertainty increases the applicability of operations research techniques that are at the core of adequate planning and scheduling policies [14]. It also enables hospitals to improve patient throughput and to reduce waiting lists (e.g., due to the shortened stay of patients). Health care funders also benefit from the cost-effectiveness of day surgery [12].

The aim of this study is to examine by means of a case study how decision support systems can contribute to an improved outpatient surgical schedule. In particular, we describe the sequencing of patients in the operating rooms of a freestanding ambulatory surgical center. In Section 2 we describe the problem setting in detail and introduce the day surgery center of interest. Next, we introduce in Section 3, a DSS that not only visualizes the problem setting, but also allows the planner to interact with advanced optimization algorithms. Using this tool, planners can fully understand their combinatorial problem and obtain noticeable improvements. We list the data that was gathered to perform the case analysis in Section 4. In Section 5, we examine and evaluate the performance of the DSS and the underlying algorithmic procedures and report on findings that cover a two-week time period in March 2008. In Section 6, we address the opinion of end-users and report on some difficulties that delay the current implementation process of the application. Section 7 summarizes the major findings of this managerial research contribution.

2 PROBLEM STATEMENT

The surgical day-care center of the UZ Leuven Campus Gasthuisberg (Belgium) accounts for about 15000 hours of total net operating time and for 13000 ambulatory surgeries annually. 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 1 depicts a floor map of the day-care center. In general, patients follow a common route through the center on their day of surgery, as indicated by the arrows. The hospital asks patients to arrive at the center approximately one hour before their planned surgery start. After a short registration at the reception, they take a place in the waiting room until a nurse accompanies them to the locker rooms where the patient can change clothes. Next, the patient is transferred to a preparation area in which pre-surgical interventions are performed, such as the placement of a catheter. After preparation, the patient is moved into a specific operating room in order to undergo surgery. As indicated in Figure 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, 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.

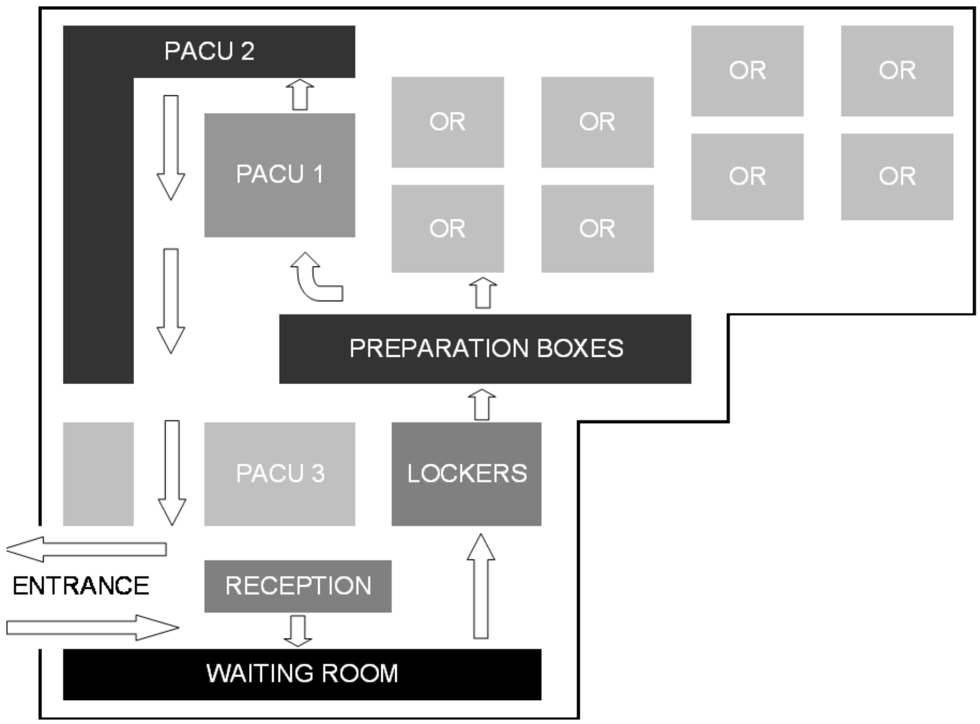

Figure 1: Floor map of the freestanding surgical day-care center of UZ Leuven Campus Gasthuisberg

Although the flow of Figure 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. Other deviations are, for instance, triggered by the type of anesthesia that is used. Surgeries that are performed under local or regional anesthesia do not require a visit to PACU 1. So, patients are immediately transferred to PACU 2 or PACU 3. Since the duration of the surgeries and the stays in recovery largely vary by type, sequencing surgeries offers the potential to reduce workload peaks in recovery. Since patients in the recovery area may arrive from any of the 8 operating rooms, these operating rooms cannot be sequenced independently.

The current procedure for scheduling surgical cases at the day-care center is based on two steps: an assignment step and a sequencing step. In 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. It should be noted 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 decision is made in the second (sequencing) step. The sequencing of the surgeries within each slot is performed exactly one day in advance. Thus the entire population of patients for that particular day, varying from 45 to 70 patients, is known to the head nurse. Although the surgeons may specify a preferred sequence, the head nurse may introduce changes to these sequences 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, significantly reduces no-shows [13]. In this research, however, we assume that the population of patients for a specific surgery day is known in advance. Thus we restrict the focus to the sequencing step, i.e. determining the starting times of the surgeries within each operating room slot. Table 1 lists the specific goals and constraints that are incorporated in the surgical case sequencing problem of interest. Note that the problem statement does not cover the processes related to the waiting room, locker rooms, preparation area or PACU 3. Further information on the description and the motivation of the multiple objectives and constraints is provided in Cardoen et al. [6].

The current sequencing approach at the day-care center results from negotiations between the surgeons and the head nurse. While surgeons limit their scope to their individual preferences, the head nurse focuses on the quality of the schedule as a whole. Although this negotiation approach has been used 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 beds, and hence may result in inferior or even unfeasible surgery schedules (see Section 5). The process is furthermore very time-consuming since the hospital lacks an efficient DSS that visualizes potential resource conflicts. We hypothesize that the introduction of the DSS should assist the head nurse in generating fair (i.e. computerized and thus less subjective) and improved surgery schedules that surpass the manual schedules.

3 DECISION SUPPORT SYSTEM

Although many researchers report on the potential contribution of a DSS for clinical decision making (see [4] for a recent overview), only limited research efforts have been directed towards decision support systems for organizational and managerial decision making in hospitals (e.g., [1], [2], [3], [16]). With the development of this DSS, we hope to increase the accessibility of optimization algorithms and facilitate the interpretation of a surgery schedule's impact on the daily working practice of the day-care center.

Table 1: Objectives and constraints of the surgical case sequencing problem at UZ Leuven Campus Gasthuisberg

Objectives	
(1-2)	Children as early as possible as it is hard for them to stay NPO before surgery ($age < 6$ and $age \geq 6$)
(3)	Prioritized patients as early as possible for medical or service-related reasons
(4)	Patients with substantial travel distance scheduled from a certain period on to increase patient satisfaction and reduce arrival uncertainty
(5)	Minimization of recovery overtime in order to avoid unplanned (and hence costly) hospitalizations or overtime for nursing personnel
(6)	Minimization of peak bed use in PACU 1 to level the workload of the nursing personnel and to protect against bed blocking
(7)	Minimization of peak bed use in PACU 2 to level the workload of the nursing personnel and to protect against bed blocking
Constraints	
(1)	All surgeries have to be scheduled in a slot that matches the surgery's slot identification, as defined by the master surgery schedule
(2)	The total population of patients for the particular day has to be planned
(3)	A surgery cannot start in an operating room when the room is still occupied by some other surgery
(4)	Patients with incomplete pre-surgical tests to be scheduled from a certain period in order to secure an amount of time to fulfill the tests
(5)	The available capacity in PACU 1 (8 beds) and PACU 2 (12 beds) is limited
(6)	Patients may request a private bed in PACU 2 (5 out of 12 beds)
(7)	Availability of medical equipment to perform surgeries is limited
(8)	Sterilization of medical equipment after surgery has to be incorporated
(9)	After surgery of MRSA-infected patients, additional cleaning requirements have to be installed

3.1 Optimization engine

We applied dedicated branch-and-bound [6], branch-and-price [7] and pre-processed mixed integer linear programming (MILP) [6] to the particular surgical sequencing problem. We examined both heuristic and exact procedures and tested their performance using an artificial test set. Results indicated that the MILP procedures outperformed the branch-and-bound procedures in solution quality. In addition, the pre-processed MILP outperformed the alternative solution approaches in proving the optimality of solutions. Consequently, we integrated the pre-processed MILP procedure into the DSS to solve the real instances of Section 5.

One major contribution of the solution procedure is in the way the objectives are normalized and aggregated into one multi-objective function. In a preprocessing step, we implicitly screen the entire set of feasible schedules to obtain a lower bound and an upper bound for each individual objective. The range between the bounds allows for an intuitive normalization of the objectives to alleviate the different units in which the objectives are expressed (e.g. beds, patients or periods). This implies that the normalized value of a single objective ranges between 0 (i.e. the value of the particular objective equals the best possible value contained in the set of feasible schedules) and 1 (i.e. the value of the particular objective equals the worst possible value contained in the set of feasible schedules). Section 3.2 introduces a graphical example to illustrate this reasoning. The normalized objectives are integrated into a multi-objective function by setting weights. The sum of the weights equals 1, so that the value of the final function also ranges between 0 and 1. If each single objective achieves its lower bound, the value of the multi-objective function is equal to 0, regardless the setting of the weights. However, due to the conflicting nature of the objectives, this is hardly ever the case (see Section 5).

3.2 Graphical user interface

We embedded the selected algorithm in a graphical user interface (GUI) to facilitate the transition from data into understandable information. The GUI is coded using the Microsoft Foundation Classes (MFC) of MS Visual C++.NET and is linked with the ILOG CPLEX 10.2 optimization library [10] to execute the algorithmic optimizations. It consists of multiple panes that visualize the detailed surgery schedule and its resulting slot utilization. The expected resource consumption is tracked over time and potential conflicts are highlighted (i.e. constraint violations). A drag-and-drop function and dialog boxes are included to allow changes added by the end-user. These adjustments range from patient-specific characteristics (e.g., incomplete medical tests, expected operating time or MRSA-infection) to the introduction or cancelation of patients and surgeries for the particular day. Each modification to the surgery schedule is evaluated using the multi-objective function. Figure 2 visualizes the detailed outcome of a schedule's performance. The DSS also provides the value for the entire multi-objective function, which takes the weighting of the individual objectives into account.

Figure 2 illustrates the 7 objectives that were introduced in Section 2 to rate a surgery schedule. For each objective an absolute value is provided as well as a relative measure. Figure 2 indicates, for example, that 11 beds are needed in PACU 2 for the proposed schedule. The corresponding bar for this objective shows that 11 beds is a rather poor performance given the existing set of feasible surgery schedules. In other words, schedules can be generated for which far less beds are needed in PACU 2. With respect to objective 5, the opposite reasoning applies: no schedule can be configured in which recovery overtime can be further reduced. The absence of a bar thus points at optimality for this particular objective, whereas a bar at its maximum length indicates

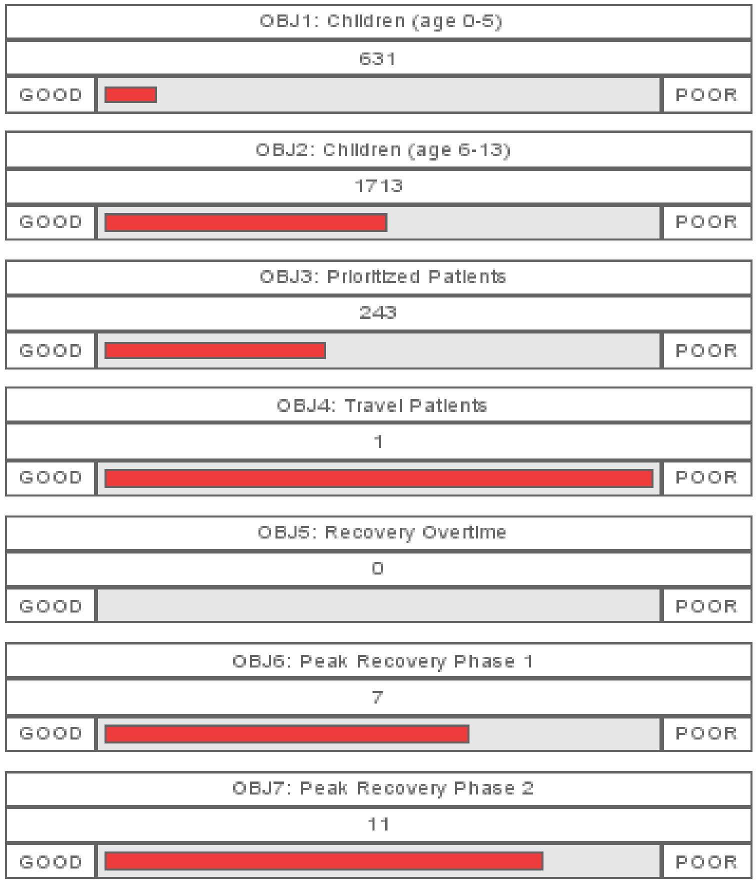

Figure 2: Representation of the surgery schedule's performance with respect to the comprised objectives

that no worse value can be found. We want to stress that the absence of a red bar does not imply an excellent result as such for the particular objective. However, it means that no feasible schedule can be found with a better performance regarding that particular objective.

4 DATA REQUIREMENTS

4.1 Data gathering

An extensive amount of data is required to study the daily surgery sequencing problem at the UZ Leuven Campus Gasthuisberg. Although most of the information was retrieved from the hospital information system, data regarding the medical equipment had to be manually collected. Below, we discuss the data that are necessary to reconstruct the underlying cyclic master surgery schedule, to list the available medical equipment, and to highlight the features of both the various surgery types and the set of patients.

- The *master surgery schedule* specifies the number and type of operating rooms, the hours that operating rooms are available, and the specialty that has priority for an operating room [5]. If we refer to these large blocks of operating room time as slots, we may reconstruct the master surgery schedule of a particular day by aggregating its constituting slots. For each slot that is registered in the hospital information system, we requested the unique slot ID, the medical discipline, the operating room to whom the slot is assigned and the day of the week on which the surgery slot is scheduled. We also captured the duration of each slot, as this number provides the original 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), since they are scheduled according to the MSS rather than workload on a specific day.

- *Medical equipment*: the data file lists for each reusable type of instrument the available capacity and the duration of the instrument's sterilization after use in a surgery. Some instruments, such as towers or lasers, do not require any sterilization, whereas others have a standard sterilization duration of 240 minutes.

- An example of the required information on *surgery types* is provided in Table 2. A surgery type ID is accompanied by a short description that facilitates the recognition of the actual work content. For each entry in Table 2, the expected operating time (EOT), stay in PACU 1 and stay in PACU 2 is reported, in addition to a list of the required medical (bottleneck) equipment to perform the surgery. The values are averages calculated using a spreadsheet that includes all surgeries performed in the surgical day-care center from 2004 to May 2008.

- *Patient-specific information*: For each patient, we retrieve the identification number (ID), the specific surgery ID (the DSS allows for comorbidity: multiple surgeries for a single patient can be performed in one surgery session), the date of surgery and the slot in which the surgery has to be sequenced (slot ID). Multiple parameters are retrieved in order 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, 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, capacity is also used, though rather sporadically, for inpatients (e.g. one-night stays or short stays).

4.2 Data problems

Trial runs of the DSS indicated some problems with the validity of the data concerning the utilization of the recovery phases, since the application indicated numerous bed capacity conflicts. This, however, conflicted with the head nurse's experience. In cooperation with the center, we identified two main reasons for the deviations. Patients who undergo the same type of surgery may differ in their recovery needs. The stay in recovery is affected by the type of anesthesia that is used. We differentiate between general, regional and local anesthesia. Patients with general anesthesia visit both PACU 1 and PACU 2. Local and regional anesthesia only imply a visit to PACU 2. Since the type of anesthesia does not solely depend on the type of surgery that has to be performed, but also on the personal request of the patient, we had to take this attribute

Table 2: Example of data file: surgery type information

Surgery ID	Discipline	Duration (minutes) EOT	PACU 1	PACU 2	Description	Instruments
...	...	...	...	...	...	...
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 ALG - RX
...	...	...	...	...	...	...

into consideration for the determination of the recovery durations. Conversely, patients who are hospitalized skip the visit to PACU 2 and are transferred to their ward in the general hospital. The results of Section 5 incorporate both corrections based on patient-specific data.

The trial runs also reported an excessive amount of instrument violations, compared to the head nurse's experience. We found that one major reason stems from the inaccurate coding of the surgery types. It is not uncommon that different surgery types may be listed under the same identification code, even though they require a slightly different set of medical equipment. The UZ Leuven is currently developing its own, very detailed, coding system to identify the different surgery types. In the future, these inaccuracies should be eliminated. Additionally, the list of instruments 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. Therefore, we adjusted the capacity levels of instruments in dialogue with the head nurse to incorporate the above situation.

5 CASE STUDY RESULTS

We tested the DSS on a 1.8 GHz Pentium 4 PC with 2 GB RAM and the Windows XP operating system. We used data from two regular weeks in March 2008. An overview of the 10 resulting instances is shown in Table 3. In the remainder of this section, we refer to these schedules as the original schedules. The number of patients (# patients) ranges from 44 to 64 and are spread over eight operating rooms (# ORs). Note that the number of slots (# slots) is always larger than the number of disciplines (# disciplines). If the number of disciplines is smaller than the number of operating rooms in use, multiple slots of the same discipline are scheduled during the day. Next to a description of the instances, Table 3 provides an evaluation of the schedule that was used on the day of surgery by the day-care center. We retrieved the sequence of surgeries as they were performed in each slot from the hospital information system and checked the schedule's feasibility with respect to the bed (Resource conflicts - bed) and instrument (Resource conflicts - instr) constraints. Table 3 also indicates the number of patients that are affected by the resource conflicts (Resource conflicts - # patients), if any occur. The results of the study can be classified into three major categories. First, it is possible that the original schedule is feasible. Second, the original schedule may not be feasible, but a feasible schedule for the particular patient population does actually exist. Third, the original schedule is not feasible, and no feasible schedule for the particular patient population can be generated. In the next subsections, we discuss these categories in more detail.

Table 3: Overview and feasibility characteristics of both the originally and optimally sequenced surgery schedules

Instance	# patients	# disciplines	# slots	# ORs	*Resource conflicts*			*Original schedule*		*Optimized schedule*		
					instruments	beds	# patients	Feasible	Value	Feasible	Value	CPU (s)
1	64	8	14	8	YES	YES	9	NO	-	NO	-	1
2	54	5	9	8	NO	NO	0	YES	0.283	YES	0.132	3
3	44	8	13	8	YES	NO	2	NO	-	YES	0	1
4	47	7	10	7	NO	YES	4	NO	-	YES	0.193	543
5	53	8	9	8	YES	NO	2	NO	-	YES	0.125	25
6	62	9	14	8	YES	YES	7	NO	-	YES	0.042	28
7	56	4	10	8	NO	YES	4	NO	-	YES	0.102	10
8	46	5	10	8	YES	YES	7	NO	-	NO	-	1
9	55	7	10	8	YES	YES	10	NO	-	YES	0.312	1921
10	57	7	9	8	NO	YES	2	NO	-	NO	-	1

5.1 Feasible Original Schedule

Only one of the ten original schedules was actually feasible, namely Instance 2. Since all constraints are satisfied, we are able to evaluate the objectives and to question whether the proposed sequence can be improved. A comparison of the outcome of the original schedule with the results for the optimal schedule indicates that the algorithmic search outperforms the knowledge of the human planner, since the value of the multi-objective function has decreased from 0.283 to 0.132 (see Table 3). Since this value is larger than 0, a trade-off between the objectives exists. A major improvement in the reduction of the peak use of beds in both PACU 1 (from 6 to 4 beds) and PACU 2 (from 9 to 6 beds) could be identified. This result is not surprising as the resulting bed occupancy is not shown by the surgery schedule itself and is hence not transparent to the planner without software support. The original schedule performs similarly to the optimal schedule with respect to the remaining objectives. Note that we obtained the optimal schedule using the preprocessed MILP procedure [6] in less than 3 seconds.

5.2 Unfeasible Original Schedule - Feasible Solution Exists

Table 3 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 (Instance 3-7 and 9). The extent of the constraint violations is expressed by the number of patients with at least one resource conflict. It should be noted that original schedules that suffer from both instrument and bed conflicts also exhibit the largest number of conflicted patients (up to 10 patients out of 55 for Instance 9). No clear structure can be identified in the type of instrument or the type of bed that 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 medical disciplines. Using the DSS, we were able to identify for each instance the optimal surgery schedule. However, the required solution time varies from 1 second to 1921 seconds. We note, however, that in the instance with the long running time, a solution was obtained in a matter of seconds; a great deal of time was required to prove optimality. A multi-objective solution value of 0 was obtained for Instance 3, which implies that every single objective is realized in the best possible way (see Section 3.1). Since the original schedules in this category are not feasible, we are unable to report on the progress in the objective function value that is achieved by the algorithmic search. One may question if we could not assess the value of the original schedules without taking the constraint violations into account. However, if we would relax the constraints (i.e. act as if there are no constraint violations and rate the particular surgery sequences), we would obtain a solution value that is by no means comparable with the optimized solution value that is reported in Table 3. Relaxing the constraints would widen the set of possible schedule configurations and hence affect the lower and upper bounds of the objectives. In other words, the lower and upper bounds of the objectives would differ between the two settings, which makes a comparison based on the normalized objective function deceptive. We refer to Cardoen et al. [6] for a mathematical clarification of the normalization function.

5.3 Unfeasible Original Schedule - No Feasible Solution Exists

The final category consists of 3 instances for which no feasible solution exists (Instance 1, 8 and 10). The original schedule determined by the human planner was also unfeasible. One should note that these instances do not necessarily result in a larger amount of patients with schedule violations, compared with the instances of the previous paragraph. The problem in Instance 10, 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. However, this service is only provided from 9 a.m. These problems, however, cannot be handled by the algorithms and require structural changes such as a switch of patients to other slots or the modification of slot starting times to make the schedule feasible. This category of instances is troublesome in practice but the DSS can assist the human planner in identifying viable solutions, i.e. making the general surgery setting feasible. A combination of a trial-and-error approach and the built-in optimization algorithms should enable the head nurse to avoid operational problems in the future; the DSS reported on the non-existence of a feasible schedule in each case in about 1 second.

It is interesting to note how the planner currently, i.e., without software support, deals with the (expected) occurrence of violations. Today, the screening and checking of the planning is mainly focused on 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 inpatient operating rooms or, instruments are cleaned by hand instead of using machines, which decreases the required sterilization duration from 240 to 20 minutes. Next to the medical equipment, problems arise with the use of the recovery bed spaces. Up to now, the planner does not adapt the surgery schedule to account for the limited available bed capacity. Table 3 confirms that this frequently leads to congestion in the PACU areas. To avoid operating room blocking, i.e., a new patient can only enter the operating room when the previous one is transferred to the PACU area, patients are prematurely dismissed by the anesthetist from the recovery areas. This practice has a negative impact on the resulting service quality. When no solution is available, the planner may cancel one or more surgeries. This, however, depends on many considerations. The outpatient surgeries, for instance, have priority over those of inpatients. Also surgeon-specific and patient-specific characteristics must be taken into account. Patients who had to change their medication in preparation of the surgery, for instance, are hardly ever cancelled.

6 DISCUSSION

Table 4 lists the main strengths of the DSS, such as the ability of end-users to direct the purchase of equipment and to justify resulting investments. However, the DSS still faces shortcomings that currently delay the actual implementation in the short term. In the next paragraphs we briefly discuss the necessity of improving the coding system, integrating information, and increasing management commitment.

Table 4: End-user evaluation of the decision support system

Strength	Weakness
• visualization leads to understanding	• doubtful accuracy estimations
• time gain for local heads of the center	• inaccurate linkage medical equipment
• user-friendly application	• no linkage with electronic patient file
• testing and comparing alternatives	• no online instrument
• developed in multidisciplinary setting	
• discussion facilitator	
• justification instrument	

6.1 Improved Coding System

The DSS is able to determine the optimal sequence of surgeries within each slot of the surgery schedule, based on estimated surgery durations. As indicated by practitioners, one might question whether these sequences are still reasonable if deviations from the estimated surgery deviations occur (i.e. the robustness of the proposed schedules). Accordingly, we registered the sequence of surgeries that was determined by the optimal schedule of Instance 2 (see Section 5.1) and replaced the estimated durations with the actual realized durations. At first glance, the results appeared promising, since 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. There was a deviation of 2 beds in the peak demand for PACU 2. We also noticed that the actual durations resulted in recovery overtime, which was not a problem in the schedule based on estimated durations.

While the surgical workload of the day was estimated to amount to 3555 minutes, its realization amounted to 4205 minutes. We examined the origin of the mismatch between the estimate and the realization of surgeries and identified two possible reasons. 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, we cannot easily justify the deterministic scheduling approach of the optimization procedures. Second, it might be possible that the durations are quite stable, but that the estimate is not accurate (hypothesis 2). We examined both hypotheses in detail for one particular surgery type of the discipline *Otolaryngology: Operations on the nose, mouth and Pharynx*, with surgery ID = 23.09 and description = *Removal and restoration of teeth - Extraction of other tooth.* A total of 1063 observations were available. The distribution of the surgery durations is well-described by a gamma function with shape $\kappa = 29.4$ and scale $\theta = 2.44$. The surgery durations are highly variable (hypothesis 1). However, the estimated duration is not uniform for each patient. Surgeons appear 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 23.09 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 underestimate the surgery duration by 15 minutes on average. In other words, their estimates do not match the actual durations. 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. In Instance 2, there was one supervisor for the three 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), this option has not been used. Based on the above discussion, we believe that hypothesis 2 constitutes the main reason of the current mismatch between actual and estimated surgery durations. Moreover, hospital management should be able to deal with this issue in the near future when the new coding system is introduced. Improving the coding system is also a prerequisite to eliminate the inaccuracy related to medical equipment planning.

6.2 Information Integration

Practitioners also report a missing link between the DSS and the electronic patient files recorded in the hospital information system. This linkage would enable a fully automated inclusion of data into the model. The surgical day-care center, though, already applies a tracking tool that monitors the progress of the surgeries during the day. Linking the DSS to the tracking tool alleviates the current problem of automated data exchange. Moreover, it would enable online (real-time) scheduling since surgery durations could be updated continuously. This would significantly improve the accuracy of the predictions that can be made for the future use of resources and thus help identify potential resource conflicts during the day. When needed, the sequences of surgeries that still are to be performed can be re-optimized under certain conditions.

6.3 Commitment of Hospital Management

Hospital management should be aware of the organizational impact resulting from changes in the operating theater practice. Recently, Hans and Nieberg [9] report on an educational tool that is applied to the operating theater setting to introduce the contribution of planning and scheduling concepts to the care managers of the future. Equivalently, the DSS can be used to improve the understanding of an operating theater's complex scheduling context and hence commit management to prioritize investments.

7 CONCLUSION

In this paper, we examined whether theoretical operating room sequencing algorithms can effectively be applied in practice. We presented a decision support system aimed at facilitating both the interaction with the settings of the problem and the interpretation of the results. We reported on the important data gathering phase and provided case study results at the surgical day-care center of the UZ Leuven Campus Gasthuisberg. By using the DSS and thus adapting the sequence of surgeries within the slots, we were able to improve the surgery schedule quality compared to the original schedules. If no feasible schedule could be obtained, the DSS proved to be a valuable instrument for testing 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 to be difficult. We discussed some major reasons for this observation, such as the coding system or the linkage with the electronic patient files. Alleviating these pitfalls should improve both the speed of implementing the DSS and the accuracy of the predicted resource consumption patterns. The key to these improvements, however, depends on the hospital manager's decisions.

Acknowledgements

We would like to thank Pierre Luysmans, Annegret Van Gool, Katrien Vromman and Werner Aerts of the UZ Leuven for their cooperation during the development of the decision support system and the validation of the case study data. Their suggestions and experience contributed to the practical value of this research. We acknowledge the support given to this project by the Fonds voor Wetenschappelijk Onderzoek - Vlaanderen as Aspirant (Brecht Cardoen).

References

[1] E. Aktaş, F. Ülengin, and Ş. Şahin. A decision support system to improve the efficiency of resource allocation in healthcare management. *Socio-Economic Planning Sciences*, 41 (2):130–146, 2007.

[2] J. Beliën, E. Demeulemeester, and B. Cardoen. Visualizing the demand for various resources as a function of the master surgery schedule: A case study. *Journal of Medical Systems*, 30 (5):343–350, 2006.

[3] J. Beliën, E. Demeulemeester, and B. Cardoen. A decision support system for cyclic master surgery scheduling with multiple objectives. *Journal of Scheduling*, 12 (2):147–161, 2009.

[4] A. Berlin, M. Sorani, and I. Sim. A taxonomic description of computer-based clinical decision support systems. *Journal of Biomedical Informatics*, 39 (6):656–667, 2006.

[5] J.T. Blake and J. Donald. Mount sinai hospital uses integer programming to allocate operating room time. *Interfaces*, 32:63–73, 2002.

[6] B. Cardoen, E. Demeulemeester, and J. Beliën. Optimizing a multiple objective surgical case sequencing problem. *International Journal of Production Economics*, 119:354–366, 2009.

[7] B. Cardoen, E. Demeulemeester, and J. Beliën. Sequencing surgical cases in a day-care environment: An exact branch-and-price approach. *Computers and Operations Research*, 36 (9):2660–2669, 2009.

[8] D.A. Etzioni, J.H. Liu, M.A. Maggard, and C.Y. Ko. The aging population and its impact on the surgery workforce. *Annals of Surgery*, 238 (2):170–177, 2003.

[9] E. Hans and T. Nieberg. Operating room manager game. *INFORMS Transactions on Education*, 8 (1), 2007.

[10] ILOG. *ILOG CPLEX Version 10.2 Documentation*, 2007.

[11] International Association for Ambulatory Surgery. Ambulatory (day) surgery: Suggested international terminology and definitions. http://www.iaas-med.com, 2003.

[12] P. Jarrett and A. Staniszewski. The development of ambulatory surgery and future challenges. In *Day Surgery - Development and Practice*, pages 21–34. International Association for Ambulatory Surgery, 2006.

[13] L.S. Lim and P. Varkey. E-mail reminder: A novel method to reduce outpatient clinic nonattendance. *The Internet Journal of Healthcare Administration*, 3 (1), 2005.

[14] P. O'Neill. Why the U.S. healthcare system is so sick ... and what O.R. can do to cure it. *ORMS Today*, 34 (6), 2007.

[15] C. Toftgaard and G. Parmentier. International terminology in ambulatory surgery and its worldwide practice. In *Day Surgery - Development and Practice*, pages 35–59. International Association for Ambulatory Surgery, 2006.

[16] S. Walczak, W. Pofahl, and R. Scorpio. A decision support tool for allocating hospital bed resources and determining required acuity of care. *Decision Support Systems*, 34 (4):445–456, 2003.