An intelligent decision support system for the operating theater: a case study

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***Abstract*—From long to short term planning, decision processes inherent to operating theater organization are often subject of empiricism, leading to far from optimal results. Waiting lists for surgery have always been a societal problem, which governments have been fighting with different management and operational stimulus plans. The current hospital information systems available in Portuguese public hospitals, lack a decision support system component that could help achieve better planning solutions. Thus, an intelligent decision support system has been developed, allowing the centralization and standardization of planning processes, improving the efficiency of the operating theater and tackling the waiting lists for surgery fragile situation. The intelligence of the system derives from data mining and optimization techniques, which enhance surgery duration predictions and operating rooms surgery schedules. Experimental results show significant gains, reducing over-time, under-time and better resource utilization.**

***Index Terms*—Operating Theater, Planning, Intelligent Decision Support System**

I. INTRODUCTION

As quality of life improves and societies live longer, health care organizations face significant increases on their demand. It is a vicious loop. Population is ageing due to better health assistance, which is supported by costly technological advances, and aged population requires increased care. These factors increase health care costs and require better management of existing resources. In this context, to maintain good service levels and patient satisfaction, health care organizations are faced with two options: either expand capacity or improve existing resources utilization. The former implies huge capital investments and is therefore, a difficult strategic decision. However, improving processes and efficiency entails an organizational development set of actions that can be performed more easily, involving less investment.

The operating theater is often considered hospitals' biggest budget consumer and revenue center in a hospital, in addition, its performance has a severe impact on society. Waiting lists for surgery are a critical issue that affect many lives, hence being constantly battled by health care organizations and governments.

In this paper, motivated by a real world case, we present an intelligent decision support system for operating theater planning scheduling, and the performance improvement achieved with it. The system was designed for two user profiles, surgeons and hospital managers, providing them a planning framework for tactical and operational problems (though we will focus on the operational level). The two main functions of the system are: (i) to provide users the means to monitor and to measure the performance of the operating theater; and (ii) to aid users devising better scheduling alternatives by supporting the task of creating better plans with data mining and optimization techniques.

Our work was integrated within a business process improvement project that took place in a large Portuguese public hospital, allowing the team to gain a fundamental understanding of the surgery scheduling process and the corresponding user needs. The project introduced us to a reality with an heterogeneous way of work across the different specialties and low guideline compliance. These behaviors result from poor organizational monitoring and lack of work flow standardization. To tackle this situation we have devised a system which helps to standardize the planning processes and to control quality and productivity.

Surgery scheduling involves taking into account different activities that are to be performed in a very uncertain environment. Such uncertainty leads to frequent deviations between what was planned and what was in fact performed. Several authors defend that the surgery schedule's quality is mainly determined by the accuracy of the surgery duration estimation [1]. Thus, in order to reduce deviations, improving duration estimates was sought in this work. Regarding surgery scheduling, we have formulated a mathematical optimization model, which allows finding the optimal allocation of patients to the available operating room shifts.

The novelty introduced in our work concerns the development of a decision support system for the operating theater and the integration of a scheduling method, involving data mining and optimization techniques. The research in this area has been extensive, however, to the best of our knowledge there is no work connecting decision support, uncertainty duration and surgery schedule optimization.

Following this introduction, we present a literature review of the features and problems addressed in this work. Section II provides a better insight into the operating theater planning problems. The decision support system, the techniques used and its implementation are briefly described in Section III and final remarks will be given in Section IV.

A. Literature Review

Operating theater planning and scheduling problems have been widely covered throughout the literature [2]–[4] and it is a still growing field of research. The most prevalent scientific community in the operating room is the operations research one, which typically studies scheduling problems. However, there is a gap between theory and practice. A Swiss survey has shown that hospital managers are not satisfied with the state of art of scheduling and Hospital Information Systems (HIS) [5]. Moreover, a recent Portuguese study also criticizes the current HIS used in Portugal, stating that they are functionally and technologically outdated [6].

Operating theater planning and scheduling is normally divided in three decision levels: (i) operational, (ii) tactical and (iii) strategic. Our work is focused on the first, which corresponds to the periodic (weekly) scheduling of patients to the available operating rooms. The tactical and strategic decision levels concern longer term decision of capacity definition and allocation to the different surgical specialties (operating room timetable, also called master surgery schedule).

The operational decision level can be organized in off-line (before execution) and on-line (during execution) scheduling. The off-line category can be further distinguished between advance scheduling, when only the surgery date is defined, and allocation scheduling, when the surgery is sequenced in an operating room. Studies focusing on off-line scheduling [7]–[10], aim to minimize overtime, maximize throughput or explore the trade-off between the cost of opening and overbooking operating rooms. Most of these studies do not include up or downstream resources, dealing just with operating rooms. Lamiri includes patient related constraints, as the deadline to perform a given surgery [8]; Guinet and Chaabane aim to minimize hospitalization costs, overtime and patient waiting time [11]; Riise and Burke add a quality of care measure and minimize the waiting time for children during mornings [12]; Jebali et al. distinguish between undertime and overtime and try to minimize both [13]. On the other hand, the online scheduling category deals with the scheduling of add-on cases [8], [14]–[17], such as emergency patients, who can not be planned in advance and whose surgery must start as soon as possible. Many studies report dedicated operating rooms for emergencies, however, this strategy implies additional costs, due to staff allocation and maintenance costs, moreover elective patients can not use these operating rooms. Lamiri considers a random portion of the OR-day capacity to serve emergency patients [8], [14]; Pham and Klinkert model the elective case scheduling problem as an extension of the job shop problem called multi-mode blocking job shop (MMBJS). The authors then describe the scheduling of emergency and urgent cases as a job insertion problem [15]; Min and Yih define the effective capacity for each surgical block, which is calculated by subtracting emergency demand and turnaround time from the planned block capacity [16].

The surgical process is characterized by strong uncertainty [1] and [18], as different sources of variability emerge from the patient arrival to his postoperative recovery. The surgery duration, including anesthesia and surgical act, is the most studied in the literature. The factor that better defines the duration of a surgery is the combination of surgical procedures [19]. Other significant sources are the main surgeon performing the procedure and his team, anesthesia type, risk class, patient age and gender [20]. Although those features can explain part of the variability, they also present a major barrier due to the large variety of procedures and the high number of surgeons in a hospital [21]. Researchers have been modeling surgical times targeting different management decisions, but most studies aim to predict surgery duration before it starts (off-line scheduling), others predict the time remaining during surgery execution (on-line scheduling) [22]. Finally, another cluster of research focuses on predicting the duration of a series of surgeries, aiming to reduce overtime [23]. However, not every management decision requires an exact point estimate, authors recognize that because of the uncertain nature of surgical procedures, it is often better to know its upper and lower bounds than a single estimate [24].

With every model and solution method developed, there is a need to bring them into practice and for that (intelligent) decision support systems have the potential to deliver them to the user. The concept of decision support systems can be summarized as information systems designed to support decision making activities. Turban [25] defines DSSs as interactive, flexible and adaptable information systems proposing possible and better course of actions to the decision maker, they aid decision agents to analyze their options and to find the best alternative among a wide solution space. These systems have long proved to be effective when applied to various domains such as health [26], where two different applications should be distinguished: (i) management DSS, oriented to organization control; and (ii) clinical DSS. The latter, concerns the executional level, where the goal is to mitigate harmful and expensive medical mistakes and help clinical staff to perform their jobs [27], for example, by providing more accurate diagnoses or safety checklists. These are patient-oriented systems, where the main objective is to improve the clinical work flow, guaranteeing patient care and safety. Intelligent decision support systems move a step further and integrate different techniques (e.g.: decision analysis through data mining) to give these applications an intelligent behavior. Guerlain identifies 7 characteristics of intelligent decision support systems: (i) interactivity; (ii) event and change detection; (iii) representation aiding; (iv) error detection and recovery; (v) information out of data; and (vi) predictive capabilities [28]. These kind of capabilities can be of extreme value to decision agents and provide new decision models to any organization.

II. Operating theater: Portuguese case study

According to a Swedish study [29], Portugal ranked 21st out of 33 European countries on providing health care services. This result was mainly influenced by the long waiting time for treatments, where Portugal ranked last. On the other hand, on electronic health services Portugal ranked 1st, due to the early, but still in progress, adoption of a national electronic health record (EHR). In 2004, as an effort to fight the long waiting list for surgery, the Portuguese government introduced a set of policies and guidelines focused on protecting patients' rights and health. This system introduced a set of waiting time limits according to the patients' priorities. Hospitals are penalized in case patients waiting time limit are exceeded. For example, a high priority patient may only wait for surgery 15 days while a normal patient sees this period extended to 270. To avoid this situation, existing resources must be used efficiently and to achieve that, surgery schedules must be carefully planned. However, we found that the current hospital information system used in Portuguese public hospitals has limited capabilities to create optimal surgery schedules or even to measure their quality. Decision making processes within the surgery theater are often empiric and the available information systems lack a decision support component, which would help achieving better results. We witnessed surgeons using different methods to devise their scheduling, such as personal agendas, spreadsheets and online calendars, reducing the level of centralization and integration within the hospital to insignificant levels. Note that it is crucial to share this information internally and with other departments, since operating theater resources are shared among different specialties and people. We reported hundreds of surgical cases being scheduled (inserted into the HIS) after the surgery itself, creating a communication issue between the different departments and the operating theater.

In general, surgeons are not very focused on operational performance and have poor sensibility for optimization, sometimes they are not even aware for how long their patients have been waiting. Even when they are estimating the duration of a surgery they tend not to be very accurate. In fact, improving the accuracy of surgery duration predictions can play a major role in increasing operating theater efficiency. When the duration of a surgery exceeds its prediction (overtime) there is a cascading effect delaying upcoming surgeries, while when the duration is overestimated leading to an early finish (undertime), valuable time is wasted idling, leading to operating room under-utilization. Our analysis has shown that 82.25% of surgeries performed in our case study between 2006 and 2010 had a relative duration deviation of over 10% from its estimation. Table I summarizes the total sum of undertime and overtime on surgeries performed in that period.

TABLE I: Summary of overtime and undertime from 2006 to 2010

	Total Time	Number of Surgeries	Average
Undertime	918.066 min	49.029	18,72 min
Overtime	2.092.461 min	33.575	62,32 min

In summary, we have observed in this hospital that there is room for improvement on surgery scheduling processes and resource management, therefore, benefiting from a decision support system to the operating theater.

III. Intelligent Decision Support System

The solution proposed to tackle the long waiting times for surgery problem is divided into three vectors discussed in this section: (i) decision support system for better information and resource management; (ii) a data mining model to predict surgeries duration; and (iii) a weekly elective patient scheduling optimization model. This approach was inspired on the work of Better et al. [30], who developed a problem solving framework integrating simulation, data mining and optimization techniques.

The decision support system was developed following an user centered approach based on the traditional software engineering life cycle model. The first task of identifying user needs and establishment of the requirements specification was conducted through a series of workshops meant to characterize the operating theater scheduling process and assess where it could be improved. The workshops were not exclusively focused on the decision support system development, but they were essential for understanding and characterizing business processes, as well as to identify the strengths and weaknesses of the current information systems. As a result of these series of workshops, a requirements specification document and a set of low resolution prototypes were produced, which were then presented and validated by key users from the hospital staff. The first trials of the system were initially deployed in two surgical specialties of the hospital as a pilot run.

Having worked closely with a hospital, many features incorporated were requested by surgeons and others were designed to overcome problems detected on the hospital information system currently in use. Another purpose of the decision support system was to integrate data mining and optimization techniques and deliver them to decision agents. The system developed is divided of 3 main modules: (i) resource management; (ii) surgery scheduling; and (iii) performance measurement.

The resource management module is to be used by the operating theater management personnel, grouping features required to define and allocate existing resources (e.g. operating rooms, medical specialties, surgeons and users of the system). The system enables not only the creation of weekly surgery schedules, but also the allocation of specialties to operating rooms (master surgery schedule), related to the operating theater tactical decision level.

The surgery planning and scheduling module is the core of the decision support system and makes available a set of features to schedule surgeries. The surgery scheduling interface supports the daily/weekly process of scheduling surgeries and was created to be as functional and easy to use as possible. This agenda shows the operating rooms available for an user's specialty and allows a weekly or daily perspective. The weekly view is an important feature, as it allows the visualization of an entire week operating room plan, which was not available before. To support the surgery scheduling process, we have integrated a data mining model that provides the user an estimative of the surgery duration and an optimization model that gives an optimal scheduling solution according to a given objective function. Figure 1 depicts an operating room's agenda and the system's optimization feature. Here, the user may select different strategies to compute the schedule. Either a dispatching rule that allocates patients on the basis of first come first served, or a mathematical model that optimizes on one of the three following objectives: maximization of the number of surgeries, maximization of the OR utilization or minimization of the waiting time.

Regarding the patients' waiting list management, two features were specially welcomed by the surgeons: a color scheme that highlights patients according to the time left relatively to the waiting time limit and the possibility of filtering the waiting list by the estimated surgical procedure time duration.

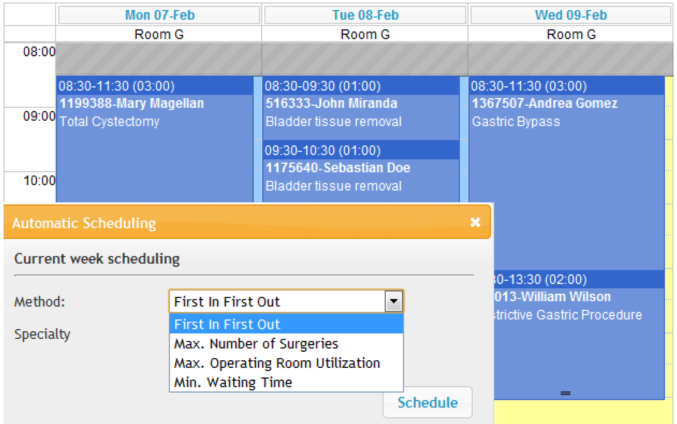

Fig. 1: Overview of the weekly surgery schedule for a certain operating room. In this particular example, each day corresponds to a different surgical specialty and each block equals a surgery and includes the patient identification, name and procedure.

The latter, gives the means to rapidly identify a surgery adequate to fill a gap in the planning horizon. Details about surgeries and patient information are also easily accessed on the interface. Finally, a non-obstructive notification system was created providing alerts when operational restrictions are violated. For example, a notification is issued when the expected time duration for the planned surgeries exceeds the limits of the period allocated to the corresponding specialty or when the scheduling violates patients' priorities. Naturally, such infeasibilities would come from manual scheduling rather than from an solution automatically generated by our DSS.

The third module concerns results evaluation through key performance indicators (KPIs), enabling identification of anomalies and opportunities to improve performance. A set of customized charts is provided, such as: operating room/specialty utilization rate over time, the evolution of patient waiting lists over time and the number of penalties due to violation of priorities throughout time. These KPIs are embedded in interactive dashboards that allow an exhaustive benchmark of performance of different surgeons, specialities and the overall operating room.

According to Guerlain's framework [28], this work fits in the intelligent decision support system cluster, as it provides the dimensions discussed on his work and goes further giving a scheduling automation feature. A minimalist overview of the sequential work flow performed by this decision support system is given in Figure 2.

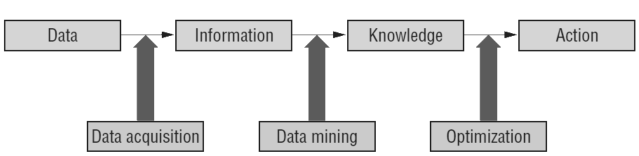

Fig. 2: Intelligent Decision Support System Process flow

The following subsections will briefly describe the techniques used to provide the intelligent behavior into the system and some of the results achieved. Two appendices were included, where these components are explored further.

A. Surgery Duration Estimation

While scheduling patients, surgeons have to estimate how long surgeries will take in order to book the operating room in advance, as it is a shared resource. Estimating surgery duration has an important impact on the operating theater schedule, since surgeons' estimates suffer from high deviation (see Table I). The problem of surgery duration estimation has been widely studied and it has been shown that the operation times can be modeled by lognormal or normal distributions. Several works have reported that the distribution of surgical procedures time can be modeled by a log-normal distribution [24]. In [31] the authors conclude that a prediction model aimed at making predictions for individual patients that includes detailed procedure codes and operation, team and patient characteristics, may be able to reduce shorter-than-predicted and longer-than-predicted OR times by 12 and 25% respectively. Therefore, the application of data mining techniques seems suitable to address this problem. Data mining concerns the automated discovery of patterns and relationships in data, also known as Knowledge Discovery in Databases (KDD). These techniques work with big and high-dimensional datasets, used to predict future behaviors by observing history. Patients and completed surgeries databases fit accurately within that description and provide a great source of data to explore (see an example for surgery durations in Figure 3).

Experiments were conducted with regression, tree-based and neural network algorithms while using or not bagging and boosting techniques. For our datasets, the best overall performing algorithm was a regression-like model that encompasses two algorithms to predict surgery durations: Bagging and M5 Rules.

Bagging stands for bootstrap aggregating, it is an ensemble meta-algorithm to improve machine learning classification and regression models stability and accuracy, by reducing variance and avoiding over-fitting. This technique generates several versions of the predicting model and uses them to get an aggregated, averaged, predictor. The different versions of the predictor are made by replicating and perturbing the learning set, causing significant changes in the predictors built [32]. The predictor used, M5 Rules, is based on a decision list built from several M5 model trees [33]. During the learning phase, in each iteration a model tree is built and the best leaf (according to some heuristic) is pruned into a rule. Instances covered by this rule are removed from the dataset, so that the process is applied recursively to the remaining instances, terminating when all instances are covered by one or more rules.

Our dataset was built using records from 2006 to 2011 and the last two years of data were separated to validate our

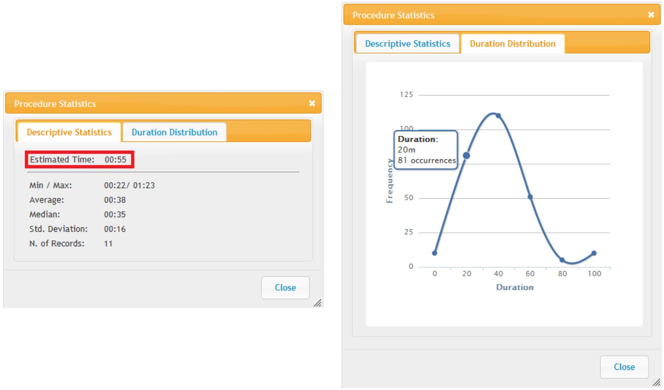

Fig. 3: Surgery duration estimation (highlighted on the left window), descriptive statistics and the distribution of the durations frequencies for a surgical procedure

results. In Appendix A the structure of the dataset (data types and fields) are presented. Experiments were conducted with several specialties and herein we report the results of two representative specialties. Experimental results were compared against surgeon duration estimates of two surgical specialties: General Surgery (**GS**) and Vascular Surgery (**VS**). Table II shows the results obtained in terms of Mean Absolute Error (**MAE**), Mean Absolute Percentage Error (**MAPE**) and Mean Squared Error (**MSE**).

TABLE II: Comparison between surgeon estimates and data mining results

	Surgeon Estimates			Data Mining		
Specialty	**MAE**	**MAPE**	**MSE**	**MAE**	**MAPE**	**MSE**
GS	70.12	38%	9336.49	47.93	32%	4784.67
VS	32.97	49%	2508.04	24.94	39%	1514.97

Both specialties watch a great improvement on the prediction accuracy. One of the reasons for poor surgeon performance derives from the time period granularity used (multiples of 10/15 minutes) as depicted on Figure 4. On the other hand, Figure 5 plots the data mining predictions against the real values, reinforcing that surgeon's granularity presents a severe constraint to fine tune schedules. Values below the diagonal line on each figure (optimal predictions) represent surgeries that went overtime, while the others were overestimated leading to operating room under-utilization. From these results it is clear that there is a strong potential gain by reducing the error in surgery estimation time with our method.

Figures 6 and 7 present two histograms that enable to compare the distributions of the overestimation and underestimation times for the two selected specialties. The results show that overestimation is more frequent and that underestimation has more extreme values. These extreme values probably correspond to cases in which the surgeon decides to cancel the surgery after the first few minutes due to unexpected factors regarding the patient condition.

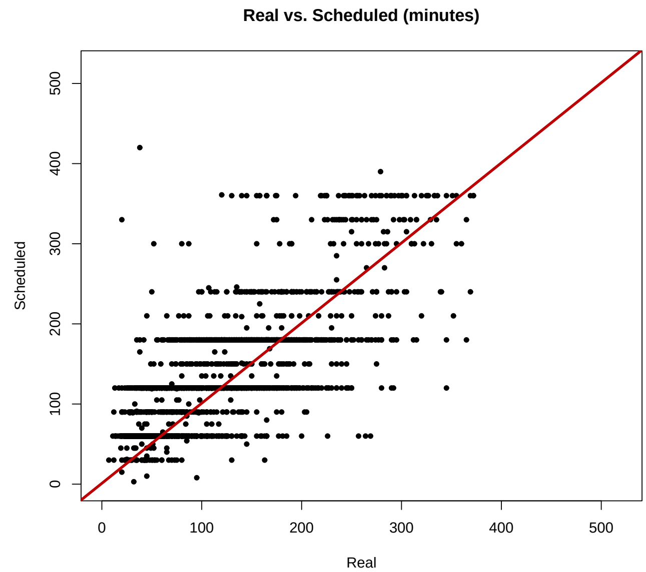

Fig. 4: Surgeon's scheduled duration vs. real duration.

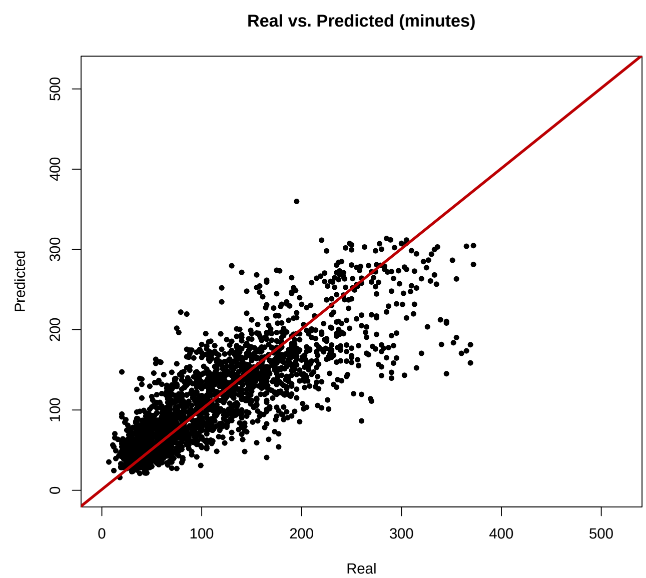

Fig. 5: Data Mining prediction vs. real duration.

B. Optimization Model

Having surgery duration accurate predictions is the first step to devise better schedules. However, there is still the need to find a combination of surgical cases that respect a set of constraints and optimizes the surgery plan. We have modeled this problem as an advance scheduling problem,

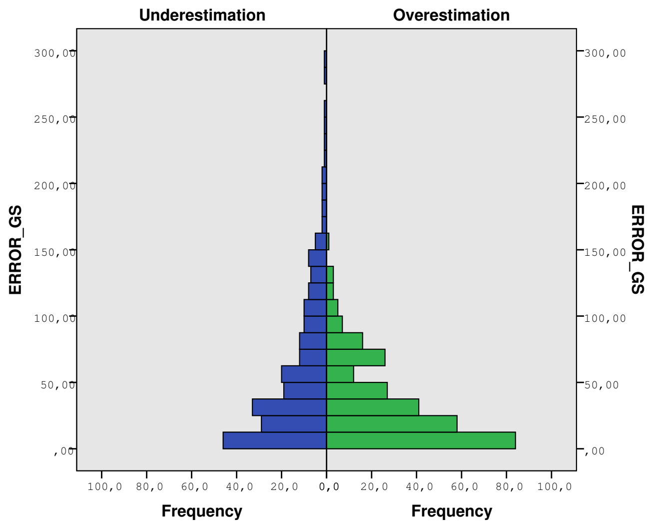

Fig. 6: Histogram comparing the distribution of underestimation and overestimation times for General Surgery.

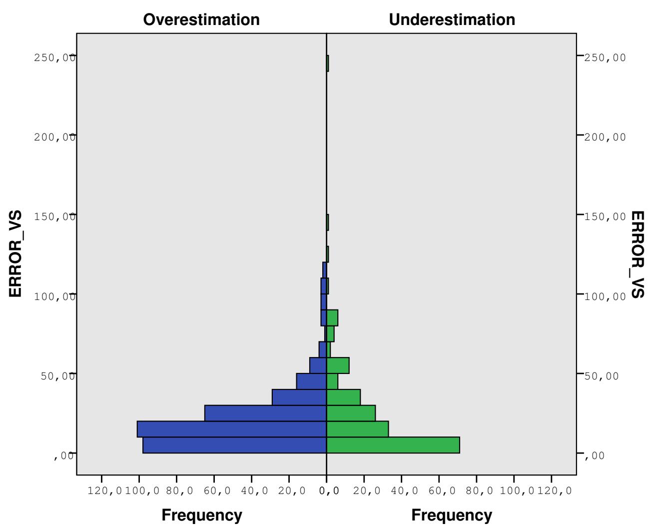

Fig. 7: Histogram comparing the distribution of underestimation and overestimation times for Vascular Surgery.

where we take the patients from a surgical specialty and assign them to a certain day of a week and operating room. Our approach is an adaptation of the multiple knapsack problem, where each knapsack corresponds to a morning or afternoon shift on an operating room in a given day. Although we formulate the model as a single-objective problem, three different objective functions are proposed and used in a row: (i) throughput maximization; (ii) utilization maximization; or (iii) waiting time for surgery minimization (days removed from the waiting list). The model's complete formulation is given in Appendix B and it is solved using CPLEX 12.2. ILOG Concert technology is used to make the bridge between the solver engine and the decision support system. We note that this commercial solver was able to efficiently solve our mathematical formulation, and therefore there was no need to come up with a tailored approximate method. Since the model only deals with elective patients (el—pat) and the problem is addressed in a deterministic fashion (det), according to the framework proposed by [34] our approach is described as:

(el — pat; date-time; iso — det — single; wait-through-util)

where *iso* means that the operating room is tackled in an isolated way, without taking into consideration downstream and upstream resources.

Computational results for the maximization of one week's number of surgeries are shown in Table III. The first column corresponds to the surgical specialty and columns 2 to 4 correspond to each objective function value. Utilization rate is calculated disregarding clean-up times between surgeries and days removed concern the sum of waiting days for surgery of the scheduled patients, therefore removed. Extended results are given on Appendix B.

TABLE III: Optimization Results - Maximizing throughput

Specialty	N. Surgeries	Utilization	Days Removed
GS	43	76.26%	13684
VS	51	70.19%	5598

The average real-world operating room utilization rates of our case study are below 70%. With our DSS, we are in fact able to increase the number of surgeries of the operating room, and it is likely that the postoperative capacity might be the binding constraint – and therefore, the schedules would have to be changed. Nevertheless, if this fact is observed, it is rather straightforward to include in the model constraints related to postoperative steps. In its current form, our model can always provide starting points to good planning solutions.

IV. CONCLUSIONS

In summary, this paper reports the development of a decision support system intended to endorse the process of operating theater scheduling. The solution presented is mainly directed to the effective management of the operating theater, where data mining and optimization components are added to allow for more efficient scheduling. To the best of our knowledge, this work is the first to combine the aforementioned techniques to reduce surgery uncertainty and to achieve a better utilization of the existing resources through scheduling optimization within decision support systems. The results shown, regarding both surgery scheduling and duration estimation, are significantly better than the current reality and can provide the end-user a great advantage when planning, compared to the methods used in the past. Extensions of the optimization model to include other upstream and downstream resources shall be considered in the future, as well as the development of a simulation component to better evaluate generated solutions.

APPENDIX A
SURGERY ESTIMATION

The data used was obtained from the patients and completed surgeries databases from the hospital, covering about 90.000 surgeries between 2006 and 2011. From our experience, administrative staff and surgeons are very prone for data insertion errors, as we have observed several cases of simple and quick surgeries lasting longer than 12 hours, resulting in the need of data cleansing. We have adopted this procedure for the two specialties for which the results are being reported since such cases were very infrequent (1.9% for GS and 0.3% for VS) and therefore would not have a significant impact in the prediction model. We stress, however, that in case of specialties such as hearth or neuron surgery this type of deviation could be natural.

Subsequently, data was divided, where the first 5 years of completed surgeries were used for building the meta-model and the remaining 2 for evaluation. We have adopted a temporal split to mirror the real world scenario in which the model is aimed at predicting the duration of future events from past records.

A mixture of patient, surgeon and procedure information was included onto the dataset, resulting in a total of 36 variables. Table IV provides a brief description of these attributes according to their type and meaning.

The results have shown that the variables having stronger influence in the model are the patient gender (#1), the patient's age (#2), the surgery priority (#3), the surgical procedure chosen (#11), the surgeon (#17) and the time estimation given by the surgeon (#35). In the context of the hospital considered all these variables are available at the time of surgery scheduling, in particular, a surgeon is allocated in advance to a patient and he is asked to provide an estimation for the surgery duration.

TABLE IV: Variables used on the prediction model

#	Type	Description
1	Nominal	Patient Gender
2	Numeric	Patient Age
3	Ordinal	Patient Priority
4	Numeric	Patient Waiting Time for Surgery
5	Nominal	Surgery Specialty Identification
6	Nominal	Surgery Month
7	Nominal	Surgery Weekday
8	Nominal	Surgery Shift
9	Nominal	Patient Diagnosed Disease
10	Numeric	Number of Interventions to be Performed
11	Nominal	Intervention Code 1
12	Nominal	Intervention Code 2
13	Nominal	Intervention Code 3
14	Numeric	Number of Surgeries to Date
15	Numeric	Number of Interventions to Date
16	Binary	If the patient has undergone surgery on other specialties
17	Nominal	Surgeon Identification
18	Nominal	Surgeon Gender
19	Numeric	Number of times the surgeon has dealt with this disease
20	Numeric	Number of times the surgeon has performed the main intervention
21	Binary	If the patient has other diagnosis
22	Binary	If the patient has any circulatory problem
23	Binary	If the patient has diabetes or renal problems
24	Binary	If the diagnosis is recidivist
25	Numeric	Duration of the last similar surgery from this surgeon
26	Numeric	Average Duration of the main procedure of this surgeon
27	Numeric	Standard Deviation of the main procedure of this surgeon
28	Numeric	Average Main Procedure Duration
29	Numeric	standard Deviation Main procedure duration
30	Numeric	Average duration of the surgery act on this combination of procedures
31	Numeric	Median duration of the surgery act on this combination of procedures
32	Numeric	Average total surgery duration
33	Numeric	Median total surgery duration
34	Numeric	Number of records with this combination of interventions
35	Numeric	Scheduled time by the Surgeon
36	Numeric	Surgery Real duration

APPENDIX B
SCHEDULING MODEL

The elective patient surgery advanced scheduling problem consists on selecting a sub set of surgeries from the waiting list and assigning them to specific time blocks across the planning week. The time blocks are previously defined and represent a period of time assigned to a surgical specialty on a given operating room (OR) and day of week. Table V summarizes the notation used in this elective patient scheduling model.

Note that according to the parameter p_i, a given patient i has a priority to go under surgery proportional to the maximum number of days that he can wait for surgery without the hospital being penalized. p_i may take the value of one, two or three, depending on whether i refers to a normal patient, a high priority patient or urgent patient.

TABLE V: Variables used on the prediction model

#	Notations
N	Set of Patients
R	Set of Operating Rooms
S	Set of Surgeons
D	Days of the week
T	Parts of the day (Morning or Afternoon)
s_i	Patient *i* surgeon
d_i	Patient *i* surgery estimated duration
w_i	Patient *i* waiting time
p_i	Patient *i* priority level
A_{rdt}	=1 in case operating room *r* in day *d* and part *t* is available, =0 otherwise
S_{sdt}	=1 in case surgeon *s* is available in day *d* and part *t*, =0 otherwise
ct	Operating Room Clean up time constant
C	Shift capacity constant

A. Decision Variables

$$x_{idrt} = \begin{cases} 1 & \text{if patient } i \text{ is assigned to the shift in} \\ & \text{day } d\text{, on operating room } r \text{ and time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

$$y_{sdrt} = \begin{cases} 1 & \text{if the surgeon } s \text{ is assigned to the shift in} \\ & \text{day } d\text{, on operating room } r \text{ and time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

B. Objective functions

As mentioned before, there are three objective functions to be optimized. The first concerns the minimization of the number of surgeries as follows:

$$Maximize f_1 = \sum_{i\in N}\sum_{d\in D}\sum_{r\in R}\sum_{t\in T} x_{idrt} \quad (3)$$

However, as more surgeries are performed, the utilization decreases since there is the need to prepare and clean up the operating rooms before a surgery, time we consider as waste. Thus, the following expression represents the maximization of the mean utilization of the operating rooms over a week span.

$$Maximize f_2 = \frac{\sum_{i\in N}\sum_{d\in D}\sum_{r\in R}\sum_{t\in T} x_{idrt} d_i}{C\sum_{d\in D}\sum_{r\in R}\sum_{t\in T} A_{drt}} \quad (4)$$

Lastly, there is also the desire to diminish the patient waiting times for surgery. In order to do that we express the maximization of the waiting time 'removed' from the waiting lists. Since high priority patients wait less and have more urgency on being operated, we have weighted the waiting time with the patient's priority level as follows:

$$Maximize f_3 = \sum_{i\in N}\sum_{d\in D}\sum_{r\in R}\sum_{t\in T} x_{idrt} w_i 10^{p_i} \quad (5)$$

1) Constraints: The available capacity of the operating rooms in terms of time, must be respected, no over-time is allowed, i.e.:

$$\sum_{i\in N} x_{idrt}(d_i + ct) \leq CA_{drt}, \forall d \in D, r \in R, t \in T \quad (6)$$

A patient can only be assigned to a room, day, part of the day, if the room is available for his specialty. Such condition is guaranteed by equation (7):

$$x_{idrt} \leq A_{drt}, \forall i \in N, d \in D, r \in R, t \in T \quad (7)$$

The patient can only be operated by his surgeon if he is available.

$$y_{sdrt} \leq S_{sdt}, \forall s \in S, d \in D, r \in R, t \in T \quad (8)$$

A surgeon can not move to different operating rooms in the same morning or afternoon.

$$\sum_{r\in R}\sum_{t\in T} y_{sdrt} \leq 1, \forall s \in S, d \in D \quad (9)$$

Since we do not allow surgeons to change operating rooms in a morning or afternoon there must be a link between patients and surgeons, so that the latter is also fixed to a shift on a operating room.

$$x_{idrt} \leq \sum_{s\in S} y_{sdrt}, \forall i \in N, d \in D, r \in R, t \in T \quad (10)$$

The final requirement expresses the domains of the variables:

$$y_{sdrt} \in \{0,1\}, x_{idrt} \in \{0,1\} \quad (11)$$

C. Further Results

TABLE VI: Optimizations results - maximize utilization

Instance	N. Surgeries	Utilization	Days Removed
GS	15	90.81%	4108
VS	23	87.65%	3003

TABLE VII: Optimizations results - minimizing waiting times (maximize days removed)

Instance	N. Surgeries	Utilization	Days Removed
GS	32	82.46%	18249
VS	45	75.63%	10477

References

[1] F. Dexter, R. D. Traub, and F. Qian, "Comparison of statistical methods to predict the time to complete a series of surgical cases," *Journal of Clinical Monitoring and Computing*, vol. 15, pp. 45–51, 1999.

[2] B. Cardoen, E. Demeulemeester, and J. Beliën, "Operating room planning and scheduling: A literature review," *European Journal of Operational Research*, vol. 201, no. 3, pp. 921–932, 2010.

[3] F. Guerriero and R. Guido, "Operational research in the management of the operating theatre: a survey," *Health Care Management Science*, vol. 14, pp. 89–114, 2011.

[4] J. Blake and M. Carter, "Surgical process scheduling: a structured review." *Journal of the Society for Health Systems*, vol. 5, no. 3, pp. 17–30, 1997.

[5] T. J. Sieber and D. L. Leibundgut, "Operating room management and strategies in switzerland: results of a survey," *European Journal of Anaesthesiology*, vol. 19, no. 6, pp. 415–423, 2002.

[6] N. P. Paulo Gomes and B. S. oes, "Análise da viabilidade económica das aplicações SAM e SAPE," Universidade Nova de Lisboa, Tech. Rep., 2009.

[7] B. T. Denton, A. J. Miller, H. J. Balasubramanian, and T. R. Huschka, "Optimal allocation of surgery blocks to operating rooms under uncertainty," *Oper. Res.*, vol. 58, pp. 802–816, July 2010.

[8] M. Lamiri, J. Dreo, and X. Xie, "Operating room planning with random surgery times," in *Automation Science and Engineering, 2007. CASE 2007. IEEE International Conference on*, 2007, pp. 521–526.

[9] H. Fei, C. Chu, N. Meskens, and A. Artiba, "Solving surgical cases assignment problem by a branch-and-price approach," *International Journal of Production Economics*, vol. 112, no. 1, pp. 96–108, March 2008.

[10] E. Hans, G. Wullink, M. van Houdenhoven, and G. Kazemier, "Robust surgery loading," *European Journal of Operational Research*, vol. 185, no. 3, pp. 1038–1050, 2008.

[11] A. Guinet and S. Chaabane, "Operating theatre planning," *International Journal of Production Economics*, vol. 85, no. 1, pp. 69–81, 2003.

[12] A. Riise and E. Burke, "Local search for the surgery admission planning problem," *Journal of Heuristics*, vol. 17, pp. 389–414, 2011.

[13] A. Jebali, A. B. H. Alouane, and P. Ladet, "Operating rooms scheduling," *International Journal of Production Economics*, vol. 99, no. 1-2, pp. 52–62, 2006.

[14] M. Lamiri, X. Xie, A. Dolgui, and F. Grimaud, "A stochastic model for operating room planning with elective and emergency demand for surgery," *European Journal of Operational Research*, vol. 185, no. 3, pp. 1026–1037, March 2008.

[15] D.-N. Pham and A. Klinkert, "Surgical case scheduling as a generalized job shop scheduling problem," *European Journal of Operational Research*, vol. 185, no. 3, pp. 1011–1025, March 2008.

[16] D. Min and Y. Yih, "Scheduling elective surgery under uncertainty and downstream capacity constraints," *European Journal of Operational Research*, vol. 206, no. 3, pp. 642–652, 2010.

[17] M. Persson and J. Persson, "Analysing management policies for operating room planning using simulation," *Health Care Management Science*, vol. 13, pp. 182–191, 2010.

[18] J. H. May, W. Spangler, D. Strum, and L. Vargas, "The surgical scheduling problem: Current research and future opportunities," *Production and Operations Management*, vol. 20, pp. 392–405, 2011.

[19] Y. Li, S. Zhang, R. F. Baugh, and J. Z. Huang, "Predicting surgical case durations using ill-conditioned cpt code matrix," *IIE Transactions*, vol. 42, no. 2, pp. 121–135, 2009.

[20] D. P. Strum, J. H. May, and L. G. Vargas, "Modeling the uncertainty of surgical procedure times: comparison of log-normal and normal models." *Anesthesiology*, vol. 92, no. 4, pp. 1160–1167, 2000. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/19762753

[21] A. Macario, "Truth in scheduling: Is it possible to accurately predict how long a surgical case will last?" *Anesthesia & Analgesia*, vol. 108, no. 3, pp. 681–685, 2009.

[22] F. Dexter, R. H. Epstein, J. D. Lee, and J. Ledolter, "Automatic updating of times remaining in surgical cases using bayesian analysis of historical case duration data and instant messaging updates from anesthesia providers," *Anesthesia & Analgesia*, vol. 108, no. 3, pp. 929–940, 2009. [Online]. Available: http://www.anesthesia-analgesia.org/content/108/3/929.abstract

[23] R. Alvarez, R. Bowry, and M. Carter, "Prediction of the time to complete a series of surgical cases to avoid cardiac operating room overutilization." *Canadian journal of anaesthesia*, vol. 57, no. 11, pp. 973–979, 2010.

[24] P. S. Stepaniak, C. Heij, G. H. H. Mannaerts, M. De Quelerij, and G. De Vries, "Modeling procedure and surgical times for current procedural terminology-anesthesia-surgeon combinations and evaluation in terms of case-duration prediction and operating room efficiency: a multicenter study." *Anesthesia & Analgesia*, vol. 109, no. 4, pp. 1232–1245, 2009.

[25] E. Turban, "Decision support systems in hospitals," *Health Care Management Review*, vol. 7, no. 3, pp. 35–42, 1982.

[26] M. Jaspers, M. Smeulers, H. Vermeulen, and L. Peute, "Effects of clinical decision-support systems on practitioner performance and patient outcomes," *Journal of American Medical Informatics Association*, vol. 18, pp. 327–334, 2011.

[27] C. Jao and D. Hier, "Clinical decision support systems: An effective pathway to reduce medical errors and improve patient safety," *Decision Support Systems*, pp. 121–138, 2010.

[28] S. Guerlain, D. Brown, and C. Mastrangelo, "Intelligent decision support systems," in *Systems, Man, and Cybernetics, 2000 IEEE International Conference on*, vol. 3, 2000, pp. 1934–1938.

[29] A. Bjornberg, B. C. Garrofe, and S. Lindblad, "Euro health consumer index," Health Consumer Power House, Tech. Rep., 2009.

[30] M. Better, F. Glover, and M. Laguna, "Advances in analytics: integrating dynamic data mining with simulation optimization," *IBM J. Res. Dev.*, vol. 51, pp. 477–487, 2007.

[31] M. J. C. Eijkemans, M. van Houdenhoven, T. Nguyen, E. Boersma, E. W. Steyerberg, and G. Kazemier, "Predicting the Unpredictable: A New Prediction Model for Operating Room Times Using Individual Characteristics and the Surgeon's Estimate," *Anesthesiology*, vol. 112, pp. 41–49, 2010.

[32] L. Breiman, "Bagging predictors," in *Machine Learning*, 1996, pp. 123–140.

[33] G. Holmes, M. Hall, and E. Frank, "Generating rule sets from model trees," in *Proceedings of the 12th Australian Joint Conf. on Artificial Intelligence*. Springer-Verlag, 1999, pp. 1–12.

[34] B. Cardoen, E. Demeulemeester, and J. Beliën, "Operating room planning and scheduling problems: A classification scheme," Katholieke Universiteit Leuven, Open Access publications from Katholieke Universiteit Leuven, 2011.