SIMULATION-BASED OPTIMIZATION FOR THE SCHEDULING OF ELECTIVE SURGERY UNDER UNCERTAINTY AND DOWNSTREAM CAPACITY CONSTRAINTS

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***Abstract*— The generation of an optimal schedule of elective surgery cases for a hospital surgery services unit is a well-known problem in the operations research field. The complexity of the problem is greatly compounded when uncertainties in the parameters are considered and is an issue that has been addressed in few works in the literature. Uncertainties appear in surgery durations and the availability of downstream resources such as surgical intensive care units (SICU), presenting large deviations from their expected value and impacting in the performance of the scheduling process. The technique presented here addresses the uncertainties in the optimal scheduling of a given set of elective surgery cases by means of simulated-based optimization. The main advantage of this approach over previous works is that detailed systems' simulations can be constructed without losing computational performance, thus improving the robustness of the scheduling solution.**

***Keywords*— Surgery cases scheduling, Parametric uncertainty, Simulation-based optimization.**

I. INTRODUCTION

Surgery is one of the most important functions in hospitals and it generates revenue and admissions to them. The operating cost of a surgery department is one of the largest hospital cost categories, approximately one-third of the total cost (Macario *et al*., 1995). Surgery is thus the area with the highest potential for cost savings. While surgery is the largest cost center, it also accounts for approximately two-third of hospital revenues (Jackson, 2002). Therefore, small improvements in efficiency could translate into significant savings and benefits to the patient as well as the hospital. For these reasons, managing the surgical resources effectively in order to reduce costs and increase revenues is one of areas that draw considerable attention of the healthcare community.

The problem of modeling and optimizing surgery operations has been documented in the literature, which can be categorized as problems of capacity planning, block scheduling, surgery scheduling and surgery sequencing. This study focuses on scheduling elective surgery patients over a planning horizon. The decision of scheduling elective surgery patients is to determine whether an elective patient should be scheduled and, if so, to determine when the patient should be scheduled. There are two challenges in this problem: capacity constraints of downstream resources such as surgical intensive care unit (SICU) beds (or ward beds) and the uncertainty in surgical operations.

The elective surgery schedule will attempt to admit as many patients as possible while satisfying resource constraints (e.g. minimizing overtime works) in order to maximize the quality of care (e.g. minimizing patient waiting time). With regard to resource constraints for scheduling elective surgeries, the consideration of operating room (OR) capacity alone does not yield good schedules. Capacity shortage of downstream resources will keep patients from moving forward and it will significantly deteriorate OR utilization. For example, when there are not enough SICU beds to accept all incoming patients, some patients have to remain in OR or should find other compatible resources, generating additional costs. Jonnalagadda *et al*. (2005) show that 15% of the total cancellation is caused by the lack of an available recovery room bed in the hospital they investigated. Sobolev *et al*. (2005) also show that patients' length of stay (LOS) in intensive care unit (ICU) and the ICU availability affect a surgery schedule. Therefore, it is important to consider downstream resource availability in addition to OR capacity.

Scheduling surgery becomes challenging when considering the uncertainty in surgery operations. Surgery operations have case-dependent durations and there is often a large variation between scheduled durations and actual durations. After surgery in an OR, LOS in a SICU is also uncertain as well. Emergency surgery is another important source that introduces additional uncertainty to the problem. To address the issue of uncertainty, stochastic optimization has been used in the surgery scheduling problems. Hans *et al*. (2008) introduce sufficient planned slacks to surgery durations for hedging uncertain surgery durations. Finally, a stochastic mixed integer programming model has been proposed for the surgery scheduling problem (Lamiri and Xie, 2006; Lamiri *et al*., 2008a,b). However, surgery durations of all elective cases are assumed to be known and deterministic, considering emergency demand as the only uncertain factor in the models. However, uncertain surgery durations may lead the solution based on deterministic durations to be infeasible. Denton *et al*. (2009) formulate the surgery scheduling problem for assigning surgeries on a given day of surgery as a two-stage stochastic linear programming. Min and

Yih (2010) utilized an L-shape method and sample average approximation (SAA) algorithm, and included downstream capacity constraints, while Yahia *et al*. (2015) included personnel constraints.

Another approach for stochastic optimization is the Simulation-based Optimization (SbO) framework. This approach originally presented in the Process Systems Engineering literature by Subramanian *et al*. (2001) applied to the optimal selection of the portfolio of drug research and development projects, proposes the combination of simulation by discrete events and deterministic and stochastic optimizations.

The SbO approach has been used in different papers presented in the literature (Subramanian *et al*., 2001, Mele *et al*. 2006, Durand *et al*. 2011 and 2012). More than a particular algorithm, it is a conceptual optimization framework for addressing problems with uncertainty, which combines the resolution of different deterministic and / or stochastic type problems in two resolution loops, one external and one internal or embedded (Durand *et al*., 2011).

The objective of this paper is to apply the SbO framework to the stochastic surgery scheduling problem while considering downstream capacity constraints (i.e. SICU beds).

II. PROBLEM DESCRIPTION

This section describes the problem that will be solved with the Simulation-based Optimization framework. For simplicity, the deterministic version of the problem will be described first, and the inclusion of uncertainty latter.

A. Deterministic Block Scheduling

Given a set I of patients waiting surgery of different specialty and a series B of available surgical blocks within an arbitrary planning horizon that consists of a set T of days, the goal of the scheduling is to minimize the total cost that consists of the patient costs and expected overtime costs by assigning all patients to surgery blocks. The scheduling also includes the decisions of how to allocate the downstream intensive care unit. Expected overtime costs are penalties that arise when a surgery block is used beyond its time limits and/or when a patient is assigned to a dummy block representing allocations to the next planning horizon. Patient costs are induced when a patient is assigned to a block, and its value depends on the urgency of the surgery case.

When a patient's surgery is finished the patient is sent to a SICU bed, where the LOS can last from 0 hours (when a SICU bed is not needed) to more than one day. The availability of SICU beds is determined by their total number and by the fact whether or not they are used by previous patients.

The planning of the surgery cases is carried by the technique called "block scheduling". In this approach, commonly used in many hospitals, each specialty is preassigned one or more surgery blocks within the planning horizon. If a patient of the list of cases to be done needs that specialty, the operation must be carried in one of those pre-assigned blocks. This method of scheduling greatly reduces the complexity of the planning, and a feasible schedule can be reached rapidly even without the use of computer assistance. However, its restrictions make the solution not as good as a one obtained with a more flexible technique. The approach presented here will need to solve a large number of scenarios, therefore the selection of this technique.

The resulting mathematical model is a Mixed-Integer Linear Problem, since it includes allocation binary variables that indicate if patient i is assigned to surgery block b, and integer variables that count how many SICU beds are in use each day.

B. Stochastic surgery scheduling problem

The randomness in surgery operations comes from the duration of the surgery, the length of stay in the SICU beds and the capacity of each surgery block debt to the possibility of having to use operating room for urgencies, but the availability of a large quantity of historical data allows to model their probability distribution in a fairly precise manner. The probability distribution of surgery length and LOS in SICU depend mainly on the specialty of the case.

In this work the uncertainties will be sampled in a set N of scenarios, large enough to represent the variability in length of surgery, LOS in SICU beds and block capacity (measured in available time). Since the allocation of patient to the blocks must be done before the real surgeries' durations are known, it is not needed to sample the decision variables modelling this stage (x_{ib}). Nevertheless, the decisions of whether to send a patient to a SICU bed or wait for one to be freed is done after the surgery, once its actual duration is known, therefore these variables have to be sampled for each scenario. Likewise, the overtime of each block is a calculated variable that also is affected by the surgeries' durations and need to be sampled.

The model describing the stochastic surgery block scheduling problem results in the following equations:

$$\text{Min } \sum_{i\in I}\sum_{b\in B_i} CQ_{ib}x_{ib} + \frac{1}{N}\sum_{n\epsilon N}\sum_{b\in B\setminus\{B'\}} CO_b o_b^n \quad (1)$$

$$\sum_{b\in B_i\setminus\{B'\}} x_{ib} = 1 \qquad \forall i \in I \quad (2)$$

$$o_b^n \geq \sum_{i\in I_b} W_i^n x_{ib} - C_b^n \quad \forall b \in B\setminus\{B'\}, n = 1..N \quad (3)$$

$$y_{it}^n \geq x_{ib} \quad t = t(b) \ldots t(b) + d_i^n, \forall b \in B_i \setminus \{B'\}, \forall i \in I, n = 1..N \quad (4)$$

$$\sum_{i\in I} y_{it}^n \leq C_t^{ICU} \quad \forall t \in T\setminus\{T'\}, n = 1..N \quad (5)$$

$$x_{ib} \in \{0,1\} \quad \forall i \in I, \forall b \in B \quad (6)$$

$$y_{it}^n \in \{0,1\} \quad \forall i \in I, \forall t \in T, n = 1..N \quad (7)$$

$$o_b^n \in \mathbb{R}^+ \quad \forall b \in B\setminus\{B'\}, n = 1..N \quad (8)$$

Objective (1) minimizes the total cost that consists of the patient costs and expected overtime costs. In the objective function, implicitly, the value of CQ_{ib} is a priority score given to a patient waiting for surgery. That is, a patient whose CQ_{ib} is higher than any others should be

Table 1. Nomenclature

Indexes and sets			
$i \in I$	Index of patient waiting for surgery	$t \in T$	Index of day
$b \in B$	Index of available surgery block	$n \in N$	Index of scenario
$i_b \in I_b$	Subset of patients whose specialty is assigned to block *b*	$b \in B_i$	Subset of blocks that were assigned to patient *i*'s specialty
$g \in G$	Index of GA generation	$p \in P$	Index of GA individual
Parameters			
CQ_{ib}	Cost of assigning patient *i* to block *b*	C_b^n	Capacity of surgical block b under scenario n in hours
W_i^n	Surgery duration for patient *i* under scenario *n*	C_t^{ICU}	Capacity of SICU at day *t* in number of beds
d_i^n	LOS in SICU for patient *i* under scenario *n*		
Variables			
x_{ib}	1 if a patient *i* is assigned to a surgical block *b*, 0 if otherwise	y_{it}^n	1 if a patient *i* occupies a SICU bed at day *t* under scenario *n*, 0 if otherwise
$OL^{p,g}$	Outer loop's objective function term of individual p of generation g	$IL^{p,g}$	Inner loop's objective function term of individual p of generation g
o_b^n	Total overtime work of a surgical block *b* under scenario *n*		

scheduled first when the surgical block capacity is enough. Since a patient's waiting time depends on his/her priority, the patient cost CQ_{ib} should be designed with care. The term modeling the expected cost is the average impact of all scenarios, therefore, it is supposed that each scenario has the same probability. Equation (2) is a patient assignment constraint. The following three constraints show capacity constraints of two resources in surgery operations; surgical blocks (i.e. OR) and SICU beds. Constraint (3) is the capacity constraint of a surgical block, and determines the total amount of overtime work. Equations (4) and (5) ensure that patients in SICU will not be over the maximum number of SICU beds at day t. Here $t(b)$ is a day t at which a surgical block b is carried on. Equations (6) to (8), defines the type of variables.

The shortage of SICU beds restricts moving patients from OR, and patients hold an OR until a SICU bed is available. Consequently, the availability of SICU beds is critical to decide the admission of elective patients.

III. SIMULATED-BASED OPTIMIZATION

With the model shown in the previous section and by enumeration, an exact solution can be obtained for a small size problem quickly and accurately. However, if the problem size gets bigger, the model becomes intractable.

In the SbO framework utilized here, the decision variables will be divided in two levels, depending on when the decision has to be done. This separation scheme is similarly done in two- and multi-levels stochastic programming techniques.

The variables that model decisions that have to be taken before the actual value of uncertain parameters is known (realization of uncertainty) are called "here and now". In the case of the surgery scheduling problem these would be the assignation of patients to surgery blocks. The rest of the decisions are made after the realization of the uncertain parameters, and the associated variables belong to the "wait and see". These variables are often called recourse variables, because they are used as a means to correct deviations from the behavior that was expected in the "here and now" level. In the present work, the variables that belong to this level are the assignation of SICU beds.

Figure 1 shows the SbO framework utilized here. The "wait and see" variables are decided in the Inner Loop where a cycle evaluates many scenarios sampling different combinations of the uncertain parameters. Since for each cycle of the Inner Loop the parameters are fixed, the optimization is deterministic. The SbO framework allows to evaluate the solution with a simulation, that will provide a better insight in the behavior of the problem. In the present work, the simulation is carried on by looping on each of the days of the horizon time and fixing the "wait and see" variables of the corresponding days. "Wait and see" variables of latter days are not fixing since the uncertain parameters of those days are not yet realized. The model in the deterministic optimization/simulation block is comprised of Eqs. (3), (4), (5), (6) and (8).

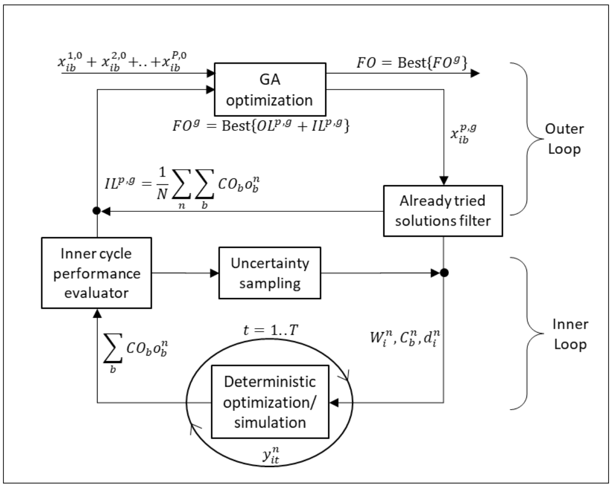

Figure 1: Simulation-based framework for the surgery scheduling problem

The “here and now” $x_{ib}^{p,g}$ variables are explored in the Outer Loop, and the total costs incurred in the assignation of patient to blocks are summed in $OL^{p,g}$ for each individual p of each generation g. Since the Inner Loop works as a function of the Outer Loop, where the ins are the “here and now” variables and the out is the expected value of all scenarios, and where there is a procedural simulation, the optimization has to be done with metaheuristic algorithms. In this paper, the selected method is a Genetic Algorithm (GA), with Eq. (1) as objective function and Eq. (2) as a constraint.

The GA takes an initial generation of individuals (each individual is a solution of the Outer Loop) and, utilizing breeding, mutation and selection operators creates successive generations of individuals, looking for better values of the objective function. The objective function, expressed in Eq. (1), is the sum of the costs from the assignation of patients to blocks (first term, represented by $OL^{p,g}$ in Fig. 1) and the expected overtime costs estimated by the Inner Loop (second term, $IL^{p,g}$ in Fig. 1). For each generation, the incumbent objective function value is the one from the best individual p found in it (FO^{g} in Fig. 1). At the end of the GA run the resulting optimal solution is the best FO^{g} of all generations.

IV. CASE STUDY AND COMPARISON

The performance of the SbO on this case study optimization was compared to the technique developed by Min and Yih (2010). The authors of this work were not able to find another hybrid simulation-optimization method for the scheduling of elective surgery under uncertainty in the literature.

A. Numerical data

Part of the data utilized in this case study was extracted from Section 4 of Min and Yih (2010). A list of 150 surgery cases to be scheduled was randomly generated following the distribution presented in that work. The number of cases was chosen on purpose to surpass the capacity of the surgery services; therefore, it was assured that not all patients could be scheduled without delay. The same surgery cases’ list was used for all optimizations in this case study.

For the Genetic Algorithm the number of generations (G) was set to 20 and the number of individuals (P) to 50, 100 and 200. The initial generation of “here and now” solutions is generated by means of sampling the uncertain parameters and solving the resultant deterministic MILP.

For the Min and Yih technique it is necessary to find the number of scenarios that provides a good solution, measured in the gap between the statistical lower and upper bounds. It was found that, for the numerical data utilized here, 200 cases give a solution of 0.49% of optimality gap. The time needed to find the number was not included in this analysis.

B. Implementation

The Genetic Algorithm used in the Outer Loop is from the GA toolbox of MATLAB R2014a. The GA of MATLAB cannot handle equality constraints when using integer variables, as in Eq. (2). So, a transformation of the $x_{ib}^{p,g}$ binary variables to integer variables has been done in the implementation, where the value of the integer variable indicates the index of the surgery block the patient is assigned to.

The Inner Loop, and Min and Yih method, is carried on in the GAMS modeling/solving software v24.2.3, with CPLEX 12.6 as MILP solver.

The techniques were implemented in an Intel Core i7-7500U computer, running at 2.70GHz with 8.00GB of RAM memory.

C. Results

Since the final best individual found by the GA can vary depending on many random samplings, for each number of individuals 20 optimizations were run. Figure 2 presents the results showing the average of the best solutions found at each generation for each group of runs. The shaded areas around each line show the range between the worst run (upper limit) and the best (lower limit). The dash-and-dot line with no markers is the result of applying the solution of the deterministic model to the Inner Loop’s performance evaluator. For comparison, the upper bound of the Min and Yih’s optimization is also included (dashed line).

It is clearly shown that the quality of the solution improves with the number of individuals employed in each run. This effect is partly based on the fact that better solutions are found when the initial generation of each run finds better individuals, and the likelihood of this increases when the population is greater.

However, a greater population implies more passes through the Inner Loop, increasing the time required for each optimization in a less linearly way with the number of individuals. Therefore, it is important to reach an equilibrium between the quality of solution and reasonable optimization times.

Table 2 shows statistics of the average of solutions found when using different population sizes. The average solution when using a population of 100 individuals is almost 21% better than when using 50 individuals’ populations, while taking 53% more time to finish 20 generations. The average time for a 100 individuals’ optimization is less than 14 minutes, that can be considered reasonable to find a better solution.

However, Fig. 2 and Table 2 show that increasing population size to 200 individuals increases the average optimization run time in almost 90% but the average solution is only 6% better. Figure 2 even shows that the range of solutions for populations of 200 individuals overlap the range of 100 individuals’ optimizations. Moreover, the average solution for a 100-population size is inside the range of solution of 200 individuals’ optimization. Therefore, it can be concluded that increasing the population to 200 individuals is not recommendable.

Table 2. Average solutions for different population sizes

Population size	Total costs [10^3 \$]	CPU time [s]
50	259.78	541.9
100	224.06	829.6
200	210.62	1567.9

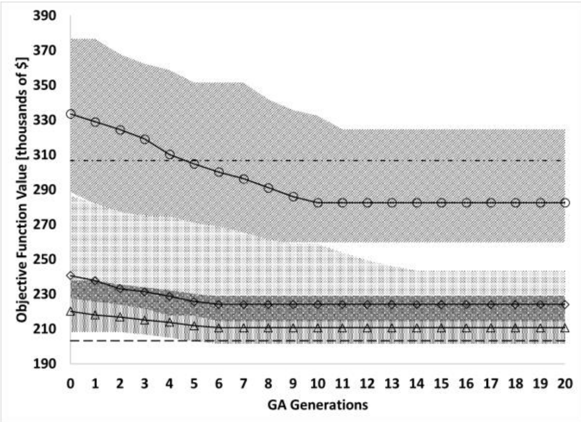

Figure 2: Average solutions and range for different population sizes. Circle marker: 50 individuals; Rhomboid marker: 100 individuals; Triangle marker: 200 individuals. Graph also includes the performance of the deterministic solution (dash-and-dot line) and Min and Yih's optimization (dashed line).

Table 3. Average statistics of SbO with a population size of 100 individuals

Concept	Value
Objective function [10^3 $]	224.06
Found in generation	6
Outer loop costs [10^3 $]	164.29 (73%)
Inner loop expected costs [10^3 $]	59.77 (27%)
Patients not allocated within horizon	71.4
Total expected overtime [hr]	76.63
Best individual found in [s]	628.9
Obj. func. of initial generation [10^3 $]	240.63

Table 4. Performance of Min and Yih's technique

Concept	Value
Objective function [10^3 $]	203.14
Assignation costs [10^3 $]	174.22 (86%)
Recourse variable costs [10^3 $]	28.92 (14%)
Patients not allocated within horizon	74
Total expected overtime [hr]	31.20
CPU time [s]	1109.5

In Table 3 are shown the average statistics of an optimization run with a population of 100 individuals. Each quantity in Table 3 was obtained by averaging the corresponding value of all runs. The mayor contribution (73%) to the objective function value comes from the costs of assignation of patients to blocks, with the Inner Loop contributing the rest. As expected, an important number of cases go into overtime (almost 77 hours), thus explaining the relatively large contribution to the total costs. Also, the great impact of the allocation variables $x_{ib}^{p,h}$ is in part due to the large number of patients that could not be scheduled within the horizon time. This result was expected because the number of patients was chosen in order to surpass the capacity of the surgery service. The penalty for delaying surgery for a patient is accounted for in the value of the CQ_{ib} parameter assigned to the dummy block, which was set to a very large number.

Table 4 shows the performance of the Min and Yih technique applied to the present problem. Although their method was able to find a better solution in terms of the objective function's value (9.3% cheaper than the average 100 individuals' solution and 3.6% lower than the average 200 individuals' ones), it does not represent a realistic situation. From Table 4 it can be seen that Min and Yih solution incurred in lower recourse variables costs, even at the expense of a more expensive assignation schedule (leaving more patients without service). For comparison, Assignation costs equate to the Outer Loop costs in SbO, and the recourse variables' level equals to the Inner Loop. The lower costs in the recourse variables' level can be achieved because all days in the schedule are sampled at the same time and at the beginning of the scenario. Therefore, the scheduler knows since the first day the duration of each surgery and LOS at the SICU beds, so, it can plan in advance how to better use the resources. This is a situation that does not happen in reality, since the scheduler cannot know, i.e., on Monday, what will happen the following days. It should be also noted that Min and Yih technique employed 33% more CPU time to finish it run.

As a final observation, although an SbO optimization run takes an average of 829.6 seconds, the best individual if generally found in 628.9 seconds, in the 6th generation. The improvement of the solution stopped at that generation even in the best run, but the runs with populations of 200 individuals show that exist solutions with lower total costs. The reason of this behavior could be a "niching" process. A niching process is a behavior found in metaheuristics algorithms where individuals converge to good solutions and stay in their vicinity, not looking for better values. For future works, a "deniching" technique (such as in Durand *et al*., 2010) can be applied to study if better solutions can be found.

V. CONCLUSIONS

In this work, the Simulation-based Optimization framework for optimization under parametric uncertainty has been applied to the problem of scheduling of elective surgery under uncertainty and downstream capacity constraints.

While the problem of elective surgery scheduling has been approached in many works, even under parametric uncertainty, the SbO framework gives the capacity to better asses the behavior of a surgery unit with the implementation of simulation. This better assessment does not resent computing performance, and finds very good solutions in a reasonable time.

Compared against to a non-simulation technique, the SbO method gives solutions with worse objective functions, but it is balanced with a more realistic modelling of the behavior of the scheduler.

In future works, the performance of the SbO framework will be compared to other techniques of scheduling under uncertainties that exist in the literature.

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