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Operating Room Scheduling in Teaching Hospitals: A Novel Stochastic Optimization Model

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Abstract

Background and Objectives: Operating room (OR) scheduling is key to optimal OR productivity. The significant uncertainty associated with surgery duration renders scheduling of surgical operation a challenging task. This paper proposes a novel computational stochastic model to optimize scheduling of surgeries with uncertain durations. The model considers various surgical operation constraints in teaching hospitals, including optimal of assigning surgeons, residents, and assistant surgeons to each surgery, infection prevention constraints, availability of surgeons, and balanced distribution of operations between various groups of surgeons.

Methods: A two-stage stochastic operating room scheduling (SORS) framework was developed to minimize idle time and over time of ORs under practical constraints. The optimization model was solved using L-shaped algorithm. The performance of the SORS in proposing optimal scheduling solutions was extensively compared with that of deterministic models, as well as the performance of manual scheduling obtained from clinical data.

Findings: Results from implication of model on sample real-life OR scheduling problems showed that SORS offers more efficient scheduling solutions as compared with the corresponding deterministic model. Furthermore, comparison of the SORS-proposed schedules with the practical schedules indicated that SORS can remarkably reduce the OR idle times (96%) and overtimes (87%), suggesting the utility of this model in clinical practice.

Conclusions: A novel validated computational OR scheduling model was developed, which can potentially be employed to achieve higher OR performance.

Keywords: Operating room scheduling, Stochastic modeling, Operations research, Hospital performance

Background and Objectives

Operating rooms (ORs) are simultaneously the largest cost center and the greatest source of revenue for most hospitals. OR planning is a key to achieving high OR productivity. Efficient OR planning is a challenging task due to the combinatorial complexity of the problem and the uncertainties associated with surgical care delivery.[1]

The last 60 years witness constant evolution of methods for improving the OR scheduling. Operational research techniques have gained an established role in such a progress. In particular, stochastic programming has proven powerful in yielding solutions for optimal management of ORs.[2-4] Denton et al developed a series of stochastic models for optimal assignment of surgeries to multiple ORs.[1] Mancilla and Storer developed a number of algorithms for appointment sequencing and scheduling of a single OR with waiting time, idle time, and overtime costs as decision variables.[2] Min and Yih developed a surgery schedule for elective patients undergoing surgery operations, which took into account the uncertainty in surgery durations and the availability of downstream resources such as surgical intensive care unit.[3] Batun et al presented a two-stage stochastic mixed-integer model to minimize the total expected operating cost under uncertain surgery duration condition. They highlighted the benefit of pooling ORs as a shared

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resource and performing parallel surgeries.[4] Zhiming proposed a two-stage scheduling approach of ORs by a multi-agent system.[5] Beaulieu et al proposed a 4-step approach to the problem. Firstly, the surgery cases are assigned to a given day. Secondly, they are scheduled based on different strategies, which are evaluated through a simulation tool in the third step. If needed, feedback and rescheduling occur in the fourth step. Uncertainty is taken into account implicitly twice: first, through the load level of the schedule built during the assignment problem, and second, in the simulation step.[6] Mancilla and Storer developed a stochastic integer programing model using sample average approximation to optimally assign surgeries to ORs and sequencing them.[7] Erdogan and Denton proposed two new stochastic linear programming models for appointment scheduling assuming that service durations and the number of patients to be served on a particular day are uncertain.[8] Pulido et al introduced a mixed integer linear programming (MILP) model for the efficient scheduling of multiple ORs during a working day considering multiple surgeons multiple types of surgeries. Stochastic strategies were implemented to take into account the uncertainty in surgery durations (pre-incision, incision, and post-incision times). In addition, a heuristic-based method and a MILP decomposition approach were proposed for solving large-scale OR scheduling problems.[9]

In teaching hospitals, where many operations are performed by residents and/or fellowships under the supervision of relevant attending surgeons, the surgeons typically do not have a list of their own surgeries in advance, thus the scheduling is carries out based on open strategy. In this paper, we present a stochastic operating room scheduling (SORS) model for daily scheduling of ORs based on open strategy. Built on the assumption that the complete set of surgeries is known in advance, the goal was set to construct a schedule that minimizes (1) the total idle times of ORs between surgeries and (2) the total overtimes across all ORs. Our model involves a comprehensive list of the real-life constraints, including optimality of assigning surgeons, residents, and assistant surgeons to each surgery, infection prevention constraints, availability of surgeons, and balanced distribution of operations between various groups of surgeons.

Methods

Two-Stage Stochastic Programming

The model is formulated as a two-stage stochastic programming model with recourse.[10] The details of model parameters and formulation are provided in Additional File 1. Briefly, the two-stage stochastic programming model involves two sets of decision variables, including first-stage and second-stage variables. This decomposition allows solving certain large-scale optimization problems, where the objective of the first-stage problem is to optimize the cost of the first-stage decision plus the expected cost of the (optimal) second-stage decision. In our modeling, the first-stage decision is to optimally assign surgeries to ORs, surgeons and assistant surgeons, and to determine the optimal sequence of surgeries in each OR and for each surgeon. The second-stage decisions include determining the start and completion times of the surgery as well as the idle time and overtime associated with each OR. The model's objective is to minimize the expected second-stage costs of OR's overtime and idle time. The uncertainties associated with surgery duration are represented by a finite set of scenarios in the second-stage problem.

Data Collection

The developed model was validated by using it to identify optimal solutions for several real-life surgical scheduling problems. These problems were formulated by collecting the data of surgical operations performed in Hasheminejad Kidney Center (HKC) within 2012-2014. Most data were extracted from the hospital information system (HIS). The required data that were not available from HIS were collected using intelligent character recognition (ICR) form that was completed by OR staff. Time data were expressed in 15-minute units. The discrete probability distributions of the surgery durations were estimated based on the surgery duration history. The overtime cost per time slot was estimated to be 2.28 k. The ORs were planned to be open 8 hours/day. The OR idle cost per time slot was estimated to be 4.41 k.

Scenarios

Representative scenarios were generated by, generating a set of 10000 scenarios through sampling from the distribution of surgeries durations, followed by clustering them into 400 scenario groups using K-means algorithm. The closest scenario to each cluster center was then used as a scenario instance. Each scenario instance was composed of collective random outcomes for the durations of surgeries. In these instances, the number of surgeries varies between 8 and 24, the number of surgeons varies between 5 and 13, and the number of available ORs is 4.

Implementation

The SORS model was used to solve a series of 30 scenario instances, representative of 1-month activity of the ORs. The allowed computation time was limited to 3 hours. For large problems that required high computational costs to reach optimal solution, the best possible solution was recorded.

The advantage of capturing uncertainty in surgery duration was assessed by determining value of the stochastic solution (VSS). VSS is the percentage of difference in the values of objective function between the stochastic and mean-value problems.[11] The mean value problem is the deterministic version of the developed model which is formulated by using deterministic variables instead of the random ones.

System and Software

The SORS model was implemented in GAMS and solved using CPLEX 12.3.0. on a 2.50 GHz, Pentium® Dual-core CPU with the Windows XP

Table 1. Comparison of the Calculated Objective Value Between SORS and Deterministic Models

Scenarios	No. of Patients	No. of Surgeons	No. of ORs	Solution Time (s)	Deterministic Model Objective	SORS Objective	VSS
1	8	7	4	70	0.000	0.000	0.0
2	10	7	4	985	4.185	0.000	100.0
3	10	7	4	1853	0.430	0.000	100.0
4	14	5	4	10800	17.520	1.368	92.2
5	14	5	4	10800	12.575	1.822	85.5
6	14	6	4	1506	4.494	0.000	100.0
7	13	9	4	10800	7.602	0.256	96.6
8	16	6	4	10800	19.673	0.664	96.6
9	14	9	4	604	1.120	0.000	100.0
10	15	8	4	10800	2.905	0.038	98.7
11	15	8	4	10800	6.234	5.148	17.4
12	16	7	4	10800	22.732	11.502	49.4
13	18	5	4	10800	6.882	0.000	100.0
14	17	8	4	2123	5.322	0.000	100.0
15	17	8	4	10800	11.358	5.388	52.6
16	16	10	4	10800	5.284	1.916	63.7
17	18	8	4	10800	7.478	0.509	93.2
18	19	7	4	10800	14.804	10.514	29.0
19	17	10	4	10800	14.145	3.910	72.4
20	21	6	4	10800	12.453	2.359	81.1
21	17	12	4	10800	4.998	0.917	81.7
22	19	9	4	10800	7.998	2.539	68.3
23	19	9	4	10800	13.513	9.617	28.8
24	21	7	4	10800	9.418	6.454	31.5
25	18	11	4	10800	3.585	1.555	56.6
26	19	10	4	10800	6.902	2.734	60.4
27	21	9	4	10800	23.769	3.864	83.7
28	22	7	4	10800	8.917	3.486	60.9
29	18	13	4	10800	5.263	0.228	95.7
30	24	6	4	10800	7.611	5.108	32.9

Table 2. Comparison of the Calculated Cost of Objective Between SORS and Deterministic Models

Scenarios	No. of Patients	No. of Surgeons	No. of ORs	Solution Time (s)	Cost of Objective	
					Practical Plan	SORS Plan
1	17	10	5	10800	83.79	0
2	12	6	3	2749	95.04	0
3	22	8	5	10800	110.55	17.64
4	16	8	4	10800	110.7	0
5	23	12	5	10800	114.96	6.69
6	21	6	4	10800	110.7	2.28
7	21	7	4	10800	97.32	6.69
8	21	9	4	10800	105.99	4.41
9	22	7	4	10800	86.22	4.41
10	24	6	4	10800	88.65	6.69
11	19	7	4	10800	123.93	11.1
12	19	9	4	10800	88.5	2.28
Average					101.363	5.1825

operating system.

Results and Discussion

Numerical Results

Table 1 compares the objective value obtained from SORS that uses random variables and a deterministic version of this model that uses mean values of variables. The fact that in all scenario instances the stochastic solution objective is lower than (97%) or equal to (3%) the mean-value solution objective indicates the superiority of the SORS compared with deterministic models. The remarkably higher efficiency of the stochastic model is further confirmed by the observation that the VSS is higher than 80% in more than 50% of the instances and higher than 90% and in 40% of the cases.

Comparison With Practical Schedules

The practical schedules of HKC's ORs were obtained from the HIS and/or ICR forms. The focus of the present study was on the training operations. Because in HKC the training operations are not performed on Thursdays and Fridays, the results of model could not be compared with practical schedules in these days. In addition, Sundays and Tuesdays are dedicated to transplant operations which are not considered training operations. By excluding the operations in these days, a series of 12 representative schedules remains for the purpose of comparison. Table 2 compares the results of such a comparison. As seen, the objective costs associated with daily schedules is largely lower for stochastic scheduling plans (average = 5.18 k) as compared with that of practical plans (average = 101 k).

Table 3 compares the idle times and overtimes of ORs between associated with SORS-based schedules and practical schedules. As seen, idle times associated schedules are remarkably lower in SORS plans (average = 13.75 minutes) as compared with the practical plans (average = 313.75 minutes) (96% reduction). In addition, the ORs' overtimes are significantly lower in SORS-proposed schedules (average = 7.7 minutes) as compared with the practical schedules (average = 60 minutes) (87% reduction).

Conclusions

In the present study a novel OR scheduling optimization model was developed. Results from implication of model on sample real-life OR scheduling problems showed that

Table 3. Comparison of idle Times and Overtimes Optimized by SORS With the Corresponding Practical Data

Scenarios	Idle Time (min)		Overtime (min)	
	Practical Schedule	SORS	Practical Schedule	SORS
1	285	0	0	0
2	300	0	45	0
3	345	60	60	0
4	330	0	90	0
5	360	15	60	15
6	330	0	90	15
7	300	15	60	15
8	345	15	30	0
9	270	15	45	0
10	255	15	90	15
11	375	30	90	15
12	270	0	60	15
Average	313.75	13.75	60	7.5

SORS offers more efficient scheduling solutions as compared with the corresponding deterministic model. Furthermore, comparison of the SORS-proposed schedules with the practical schedules indicated that SORS can remarkably reduce the OR idle times and overtimes, suggesting the utility of this model in clinical practice.

Abbreviations

(OR): operating room; (SORS): Stochastic operating room scheduling; (HKC): Hasheminejad Kidney Center; (HIS): hospital information system; (ICR): intelligent character recognition; (MILP): mixed-integer linear programming; (VSS): value of stochastic solution.

Competing Interests

The authors declare that there are no conflicts of interest.

Authors' Contributions

MMS and PS jointly designed the study. AA has the major contribution to developing the SORS and the solution method, analyzing the data, and drafting and revising the manuscript. MMS contributed to preparing and revising the manuscript. PS determined the constraints of the model, the setting, and interpretation of the results. All authors read and approved the final manuscript.

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Additional files

Additional File 1 contains the details of the two-stage stochastic programming model.

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