Chapter 11
Risk-Aware Scheduling of Elective Surgeries

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Abstract This paper addresses Operating Room scheduling problems in elective surgery. In particular, we study a model for determining the surgical schedule when uncertainty on surgery duration is taken into account in order to consider and evaluate the risk of overtime and the possible waste of operating time. Surgical cases are selected from the waiting lists according to several parameters, including surgery duration, waiting time and priority class of the operations. We apply the proposed approach to the operating theatre of a public, medium-size hospital in Italy, using Mathematical Programming formulations and Monte Carlo simulations, assuring the scalability of the approach on larger hospitals.

11.1 Introduction

The operating theater (OT), consisting of several operating rooms (ORs), is one of the most critical resources in a hospital because it has a strong impact on the quality of health service and represents one of the main sources of costs (surgical teams, equipment etc.). Given the patients' waiting list and various information on OT characteristics and status, OT planning problems consist in deciding the schedule

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of surgeries in a given time horizon, with the aim of optimizing several performance measures such as OR utilization, throughput, surgeons' overtime, lateness etc. [2,7–9,12].

Surgical cases are usually carried out in OR sessions, i.e., uninterrupted time blocks (typically, half day or a full day). In the management policy usually referred to as *block scheduling*, each OR session is devoted to a specific surgical discipline. This organizational solution is often preferred, since performing the same discipline in a given room during a given time span typically simplifies the physical handling of equipment and/or materials. A more flexible solution is the *open scheduling* policy [3], in which no pre-specified session-to-discipline assignment exists, so two cases corresponding to different disciplines can be scheduled in the same OR session. This paper focuses on the block scheduling policy. Thus, surgical planning in operating theaters can be seen as involving three distinct decision steps:

(i) Deciding the surgical discipline that will be performed in each OR session;
(ii) Selecting elective surgeries to be performed in each OR session;
(iii) Sequencing surgeries within each OR session.

Problem (i) is often referred to as the Master Surgical Scheduling Problem (MSSP), and returns the Master Surgical Schedule (MSS). Problem (ii) determines the Surgical Case Assignment (SCA), and is therefore denoted as Surgical Case Assignment Problem (SCAP). Problem (iii) outputs the detailed calendar of elective surgeries for each session. Literature on all three above decision levels is wide and growing, and it has thoroughly been reviewed by several researchers [1,15,16].

The three above decision problems have been addressed by a multiplicity of approaches. Research focused on either all three levels concurrently, two of them, or even single problems. Some approaches have been designed to fit specific issues that may or may not be present in various real-life settings. In this paper we focus on SCAP considering uncertain durations of surgeries. Our assumptions are similar to those proposed by Agnetis et al. [1], who design a deterministic model for MSSP and SCAP, on the basis of the current state of the waiting list. Their approach consists in concurrently defining the MSS and the list of surgical cases to be performed during each OR session over the planning horizon, whereas we consider the MSS as given and focus our analysis on the SCAP.

The main contribution of this paper is to assess the risks of overtime and possible waste of operating time in each operating session associated with an OR plan obtained through a deterministic optimisation model. This analysis allows to evaluate the impact of uncertainties in the surgical times when the solution of the deterministic model is implemented. The role played by the variability in surgery times in creating delays, resources waste and non-compliance in health care is documented in the literature, but is often ignored in OR planning and scheduling systems. Completely ignoring this kind of variability, i.e., using the basic assumption of deterministic times, could be unrealistic and rather optimistic from the start, generating schedules that promise more than can be delivered to both customers and managers of the health care system [5,6].

The analysis conducted in this study yields two main advantages: it evaluates the risk associated with a specific OR plan, and gives sufficient information to take suitable decisions in the operational plan to limit risks and/or reduce costs; e.g., using overtime or processing additional case surgeries. Based on these considerations, the output of this analysis provides a more realistic view of a specific OR plan performance. Moreover, it could suggest and justify some improvements in the planning system to take into account the risks associated to the times variability in the assignment process.

The remaining sections are organized as follows: Sect. 11.2 introduces the addressed problem; Sect. 11.3 describes the setting adopted in our computational experiments and reports on the results obtained. Section 11.4 draws some conclusions, outlining perspectives for future research.

11.2 Problem Description

The aim of this work is to design a decision support tool for the risk assessment in elective surgical planning. We assume that the MSS is given. The OT management provided us with the MSS currently adopted by the hospital; therefore, only the SCAP has to be solved. Note that, once a MSS is determined, it identifies which OR sessions are assigned to each surgical discipline; so, a distinct SCAP can be solved for each discipline independently from the others.

Following [1], we associate a score K_{is} to each surgical case i of discipline s, defined as $K_{is} = P_{is}(W - R_{is})$, where P_{is} denotes the *nominal* surgery duration, W corresponds to the maximum allowed waiting time for the least urgent surgeries (as prescribed by regional regulations), and R_{is} is the *slack time*, i.e., days to the due date. To assign elective surgeries to OR sessions, we maximize the score associated to the selected surgeries, accounting for their priority class as well as for their duration. Let Q_s be the number of OR sessions assigned to surgical discipline s by the actual MSS, and T_{hs} the duration of the h-th OR session of discipline s, $h = 1,\ldots,Q_s$. We introduce the binary decision variables x_{ish} such that $x_{ish} = 1$ if the i-th surgery of discipline s is assigned to the h-th OR session of discipline s, otherwise $x_{ish} = 0$. Then, the optimization problem can be formulated as follows:

$$\max \sum_s \sum_h \sum_i K_{is} \cdot x_{ish} \tag{11.1}$$

$$\sum_h x_{ish} \leq 1 \qquad \forall i,s \tag{11.2}$$

$$\sum_i P_{is} \cdot x_{ish} \leq T_{hs} \qquad \forall s,h \tag{11.3}$$

$$x_{ish} \in \{0,1\} \qquad \forall i,s,h \tag{11.4}$$

where constraint (11.2) guarantees that each surgery is performed at most once, while constraint (11.3) sets a maximum duration for the surgical cases assigned to the same OR session.

When addressing this problem, the surgery duration is commonly supposed to be deterministic and known in advance, based on estimates provided by surgeons: in fact, for each surgical case in the waiting list, a nominal (i.e., fixed) duration is specified (P_{is}). However, the whole surgical process is affected by uncertainty, so different surgical durations can be observed in practice. This may result in OR underutilization, if surgeries last less than expected, or overtime, if the actual surgery duration is higher than planned; both cases lead to inefficiencies in the OT management, and may significantly affect the patients' service level. Therefore, it is important to evaluate the risk associated to a deterministic planning. To this aim, we propose a statistical analysis on the surgical records for each discipline. More specifically, for each type of surgery appearing in the surgical records—coded according to the classification of surgical procedures International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM, [11])—we collect the actual duration of each surgical case over a period of 1 year; then, we fit a probability distribution on these data and estimate its parameters.

In this way, for each surgical case, we associate a probability distribution to its surgical duration. Then, we run Montecarlo simulations to derive several realizations of surgical durations for a given surgery. We now plug these alternative observations into the solution of the deterministic formulation (11.1)–(11.4) for SCAP, to evaluate the possible variation of the makespan related to each filled OR session.

Evaluating the solution obtained by the deterministic planner on a set of alternative scenarios enable us to assess the related risk of overtime/underutilization of each OR session. More specifically, once the SCA has been generated, this solution is implemented in a number replicates of the instance under study taking into account the possible surgery times variability. The results of this simulation enables to conduct a probabilistic analysis to estimate the distribution of the makespan of the OR sessions associated with the specific SCA solution. This analysis allows the decision maker to evaluate specific risk measures including the probability of meeting specific targets on the SCA performance.

11.3 Computational Experiments

This section describes the computational experiments that we ran for the OT of a medium-size Italian hospital in Tuscany. We first present our experimental setting (Sect. 11.3.1); then, we discuss the results obtained.

11.3.1 Experimental Setting

The hospital's OT performs elective surgeries for the following disciplines: general surgery, paediatric surgery, otolaryngology, urology and gynaecology. For the sake of brevity, our experiment focuses on a single surgical discipline; namely, general surgery. Nevertheless, since the SCAP can be solved separately for each discipline, our risk assessment method is equally applicable to any surgical discipline, without affecting the results obtained for the other disciplines.

Model (11.1)–(11.4) is solved using CPLEX 12.4 on a 1.8 GHz Intel Core i7 with 4 GB of RAM. Based on a preliminary experimental campaign, we truncate the solver after 5 min of computation; the optimality gap w.r.t. the best solution found is on average 0.7 %. From a computational viewpoint, we work with 1-min temporal grain and, compared to [1], we do not discretize time in 15-min time units.

The hospital provided us with the surgical records associated to 1,470 cases from general surgery performed in the last months. Based on the MSS adopted by the hospital, $Q_s = 13$ OR sessions are assigned to general surgery ($s =$ gs) in 1 week. In particular, there are 10 full-day sessions, each lasting 10 h (so $T_{hs} = 600$ min, for $h = 1,\dots,10$), 2 morning sessions, each lasting 6 h (i.e., $T_{hs} = 360$ min, for $h = 11,12$), and one afternoon session, lasting 4 h (i.e., $T_{hs} = 240$ min, for $h = 13$). From each OR session capacity we leave a planned buffer time for possible delays and/or uncertainties affecting surgery duration: we considered two buffer time values; namely, $0.1T_{hs}$ and $0.2T_{hs}$ ($s =$ gs, $h = 1,\dots,13$).

Several researches in the literature suggest that surgical duration usually follows a lognormal distribution [13, 14, 17]; alternatively, it may follow a Weibull distribution [4, 5, 10]. For this reason, we selected these two families of probability distributions in our tests: for each surgery type, we fitted both distributions to our data, and identified their parameters (mean and standard deviation for the lognormal distribution, scale and shape parameters for the Weibull distribution) through Maximum Likelihood Estimation (MLE). Further, we used our data from surgical records to estimate a truncation point cutting the right tail off: in fact, using a truncated probability distribution appears reasonable, since surgical duration higher than a given threshold will (almost) never occur. Validating both models supported the hypothesis that surgical duration follows a lognormal distribution for almost all surgical classes in general surgery.

We use information collected through our statistical fitting for quantifying risk associated to the deterministic SCAP on a number of test instances. In particular, we build $M = 10$ test instances by sampling (with replacement) $N = 300$ surgeries from the historical data provided by the hospital. Each instance represents a possible realization of the waiting list that can be given as input to solve the SCAP. Once a deterministic solution is obtained, it is evaluated on stochastic surgical durations sampled from the corresponding distribution; i.e., for each surgery included in the SCAP solution, we replace its nominal duration by a set of (say) $n_t =$ 1,000 stochastic realizations extracted from the estimated probability distribution associated to that surgical case. We repeat this procedure for each of the M test instances.

Notice that, in general, surgical duration for each class can be characterized by a different distribution. This would prevent us to identify a closed-form expression of the distribution for the proposed risk assessment procedure.

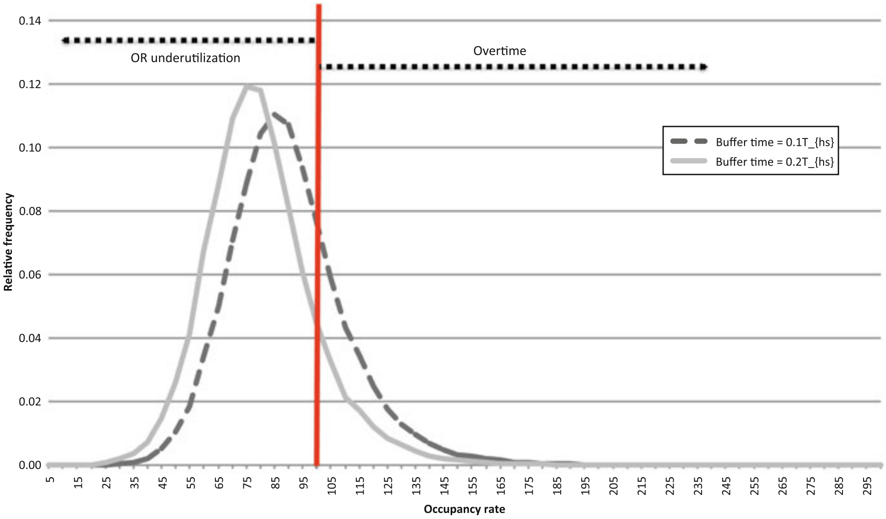

Fig. 11.1 Histogram of OR sessions occupancy rate for different buffer time values: $0.1T_{hs}$ (*dashed curve*) and $0.2T_{hs}$ (*solid curve*)

11.3.2 Results

As discussed in Sect. 11.2, we ran our Montecarlo simulations to derive n_t alternative scenarios of actual surgery duration for the SCAP deterministic solution. Based on the simulation outcomes, we measured the occupancy rate of each OR session in the M instances, w.r.t. the maximum capacity of each OR session. The results obtained are summarised in Fig. 11.1.

Figure 11.1 shows the histogram plot associated to the OR sessions occupancy rate, including both buffer time values. The vertical line at $x = 100$ corresponds to full occupancy rate; lower values imply underutilization of ORs, while higher values denote overtime. This plot provides an overview on OR utilization, including all the M instances and for all the OR sessions. This figure, reporting aggregated data, effectively describes the type of variability associated with the use of a deterministic planner when surgical times are affected by uncertainty. Note that the curve associated to a higher buffer time is shifted to the left w.r.t. the other curve, showing higher exposure to OR underutilization. On the other hand, comparing the two curves to the right of the vertical line, we note that overtime occurs more frequently when the buffer time is smaller, thus underlining that such a buffer is not big enough to deal with possible delays in surgery duration. When the risk of overtime is very high, and the expected delays are significant, the OT management may decide to postpone some surgical cases to the next working days. This would help to save additional costs to the hospital and further inconvenience to patients,

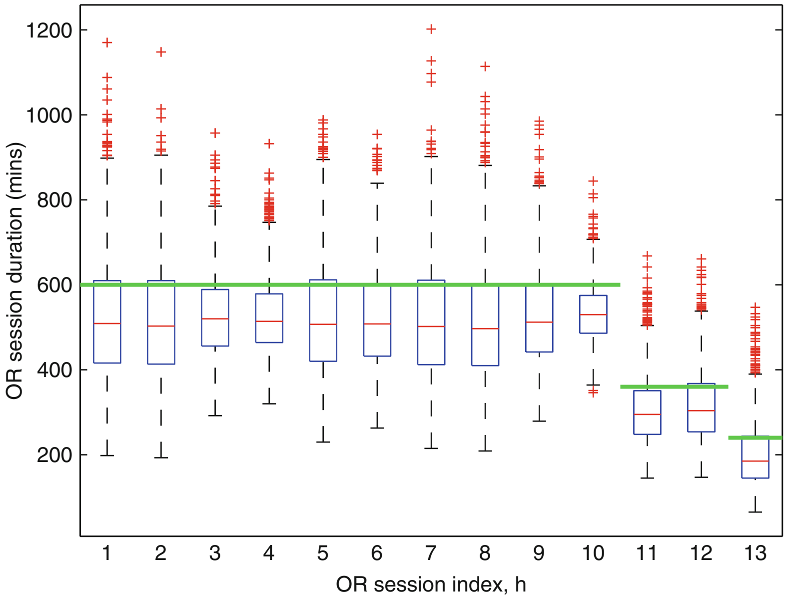

Fig. 11.2 Box plots on a sample test instance (# 1), with a buffer time of $0.1T_{hs}$

which would have resulted instead from a deterministic planning. The overall behavior described may suggest the decision maker to intervene in different ways: to adequately arrange overtime; to make ORs readily available when not in use, and to adopt techniques to reduce the variability of surgical times [5,6]. On the other hand, the scheduler may consider some changes to the models in use so that they can take into account the variability of the surgical times. However, these observations suggest a compromise between modeling improvements and the efforts dedicated to reduce that variability.

A deeper look into a single instance (say, instance #1) is provided by Figs. 11.2 and 11.3. These two figures provides box plots of surgical duration (expressed in minutes) for the Q_s OR sessions allocated to $s =$ gs; the former is based on a buffer time of $0.1T_{hs}$, while the latter uses a buffer time of $0.2T_{hs}$. The tick horizontal lines denote the capacity T_{hs} of each OR session $h = 1, \ldots, 13$.

These two figures show the information that the decision maker can use to evaluate how to organize resources and activities within the surgical block. On the basis of his/her aversion to overtime, the decision maker will be willing to use a certain level of buffer time in the optimization model; this choice has direct consequences on the possibility of OR underutilization.

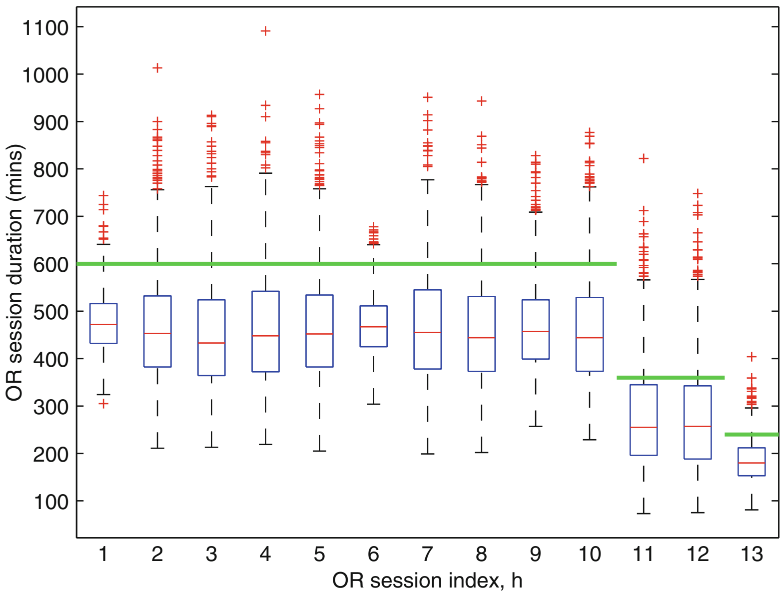

Fig. 11.3 Box plots on a sample test instance (# 1), with a buffer time of $0.2T_{hs}$

11.4 Conclusions

This paper is devoted to assess risks of overtime and possible waste of operating time associated with an OR plan obtained through a deterministic model for the SCAP. The proposed analysis allows to evaluate the impact of uncertainties in surgery times when implementing the solution of the deterministic model. A critical issue in applying our method relies on the availability of surgical records to provide accurate estimations of the statistical distributions for surgical times. Moreover, a careful preprocessing might be required, to manage possibly wrong or incomplete data records. This approach is equally scalable to larger hospitals, whose OT size may impact on the optimization methods adopted to solve the OR planning problem.

The output of the analysis suggests different actions to the decision maker, mainly related to the following issues: overtime administration, management of operating rooms become available throughout an OR session; methods to reduce surgical times variability. Further, the analysis can motivate some changes in the optimization models in order to exploit the variability of surgical times in the planning phase.

The results of this study highlight the significant impact uncertainty has on OR planning and scheduling, motivating the need for a decision support tool explicitly accounting for stochastic components affecting the planning activity. A set of easy-to-read indicators could be included to summarize the results in a compact and effective way, thus facilitating OT management decisions. Future research directions will also cover risk assessment methods in OR planning, introducing adequate risk indicators and identifying a trade-off between modeling improvements and efforts dedicated to uncertainty management.

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