Long term evaluation of operating theater planning policies

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Abstract

This paper addresses Operating Room (OR) planning policies in elective surgery. In particular, we investigate long-term policies for determining the Master Surgical Schedule (MSS) throughout the year, analyzing the tradeoff between organizational simplicity, favored by an MSS that does not change completely every week, and quality of the service offered to the patients, favored by an MSS that dynamically adapts to the current state of waiting lists, the latter objective being related to a lean approach to hospital management. 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 models to the operating theater of a public, medium-size hospital in Empoli, Italy, using Integer Linear Programming formulations, and analyze the scalability of the approach on larger hospitals. The simulations point out that introducing a very limited degree of variability in MSS in terms of OR sessions assignment can largely pay off in terms of resource efficiency and due date performance.

Key words: surgical planning, operating room scheduling, master surgical schedule, surgical case assignment

1. Introduction

The operating theater (OT) 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 (see Sobolev et al. [13], Cerda et al. [3]). The OT is the core resource of the patient's surgical pathway. The way such complex and costly resource is managed affects the quality of the whole process undergone by surgical patients. Several operating rooms (ORs), possibly with

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different characteristics, are managed in a single OT and may be shared among different surgical disciplines. An OR session is a time interval (e.g. Wednesday from 8am to 2pm) devoted to a surgical discipline in an OR. In this study we are concerned with elective surgeries. However, as described later, such allocation can also indirectly take into account possible emergencies.

In a given time period, the OT managers are faced with complex decision problems including:

(i) assigning surgical disciplines to operating room sessions over time,

(ii) assigning elective surgeries to operating room sessions,

(iii) sequencing surgeries within each operating room session.

Problem (i) is a tactical level problem, and it is often referred to as Master Surgical Schedule Problem (MSSP) [2], its output being the Master Surgical Schedule (MSS). Problems (ii) and (iii) are operational problems. The former determines the Surgical Case Assignment (SCA) [16], and is therefore denoted as Surgical Case Assignment Problem (SCAP). The latter outputs the detailed timetable of elective surgeries for each day. We refer to this problem as Elective Surgery Sequencing Problem (ESSP). Given the patients' waiting lists and various information on OT characteristics and status, these problems aim at optimizing several performance measures including operating room utilization, throughput, surgeons' overtime, lateness etc.

In the last years, operating room planning and scheduling problems have been studied by several researchers, as reviewed in the comprehensive surveys by Cardoen et al [2], Guerriero and Guido [8], Sier et al. [12]. Several papers address the above problems separately (e.g. Testi et al. [14], that use a sequential three-phase approach to determine the MSS, the SCA and the detailed surgery sequencing), or focus on a single problem (e.g. Blake et al. [1], Van Houdenhoven et al. [21], Sier et al. [12]).

In other studies, the problems are concurrently addressed, e.g. Testi and Tanfani [15] propose an Integer Linear Programming (ILP) model for concurrently solving MSSP and SCAP, and in a follow-up paper [16] they introduce a pre-assignment heuristic to reduce problem size. Dexter and Traub [4] address SCAP and ESSP on a number of pre-selected surgical cases, while Marques et al. [10] and Molina and Framinan [11] apply a similar approach to real cases. Herring and Herrmann [9] propose a surgery scheduling approach which re-assigns unused operating room time to account for new high priority cases and make more equitable waiting list decisions. Recently, a growing number of models relate surgical planning decisions to the broader patient pathway, including e.g. bed occupancy considerations in the wards (Vanberkel et al. [19, 20], Evers et al. [5], Van Oostrum et al. [18]), or other issues such as surgeons and assistants training plans (Ghazalbash et al. [6]).

In this paper we investigate the effect of various MSS policies on the quality of the surgical plans that can be attained. We do this by simulating the system's behavior throughout one year, i.e., solving every week MSSP and SCAP, by means of a suitable model that reflects the MSS management strategy. In many hospitals, the same MSS is employed throughout several months, or a whole year. With a constant MSS, bed occupancy is more predictable and physicians' schedule is repetitive, which simplifies the overall organization. On the other hand, leaving more flexibility in defining the MSS expectedly results in more efficient resource utilization and allows to better follow the dynamics of the waiting lists. In recent years, as a growing number of hospitals re-engineer their processes according to the *lean* concept (see e.g. Graban [7]), much more attention has been paid to the fact that the patient flow should pull the delivery of services – surgical operations in this case. Ideally, therefore, all obstacles (such as getting stuck to a predetermined MSS) to a direct link between demand and service delivery should be removed. In our study we propose modeling and algorithmic tools for evaluating the benefits stemming from a dynamic MSS. We validate the model on data concerning San Giuseppe hospital, a medium-size Italian hospital, located in Empoli (Tuscany).

The paper is organized as follows. In Section 2 the problem is described in detail. In Section 3 the mathematical formulations are introduced. Computational experiments concerning the case study are illustrated and discussed in Section 4. Finally, in Section 5 some conclusions are drawn.

2. Problem description

This study focuses on the evaluation of various approaches to defining the MSS over time. OT managers are typically interested in long-term planning *stability* and *flexibility*. Stability refers to personnel having a repetitive, predictable schedule, which is typically preferred since it allows a simpler scheduling of personal engagements. Also, a stable schedule allows a more predictable pattern of bed occupancy in the pre- and post-operative rooms as well as in the wards. Flexibility concerns the ability to dynamically adapt the weekly plan to the evolution of the waiting lists, which may avoid imbalances among the quality of service perceived by the patients of various disciplines, and may also allow for a more efficient utilization of the operating rooms. Stability and flexibility are potentially conflicting, since the former pushes towards having a constant MSS, while the latter might benefit from changing the MSS over time. Different organizations may have different capabilities of adjustment to a changing MSS, therefore the right *tradeoff* between flexibility and stability has to be found.

From the viewpoint of this tradeoff, the two extreme policies consist in keeping the MSS fixed throughout the year or, respectively, recomputing it every week from scratch. In between these two policies, one may allow periodic but limited changes in the structure of the MSS. Let the *distance* between two given MSSs be the number of operating rooms, for each OR session, which are assigned to different surgical disciplines across the two MSSs. For instance, let us assume that, for a given MSS, surgical discipline s_1 will be performed in operating room j on Wednesday morning (i.e., 8am–2pm); then, a new MSS having distance 1 from the original MSS can be obtained by assigning a different surgical discipline s_2 to the same operating room j on Wednesday morning, and leaving the rest of the MSS unchanged.

Hence, we can define an *MSS change policy* as the policy of keeping the same MSS for blocks of b weeks, and allowing changes only with respect to a *reference MSS*. When the MSS changes, we require that the distance between the new MSS and the reference MSS does not exceed a value Δ, providing a trade-off between stability and flexibility. OT managers will identify a suitable value for the maximum distance Δ, based on their attitude towards either higher stability (corresponding to smaller Δ-values) or higher flexibility (supported by higher Δ-values). Actually, we consider two possibilities for the reference MSS. It can be either the MSS of the previous block (*dynamic change policy*) or a given MSS which does not change over time (*static change policy*). We refer to a dynamic (static) change policy as $D(b, \Delta)$ ($S(b, \Delta)$).

We next describe the distinctive features of the problems we deal with.

All elective surgeries are grouped into *surgical disciplines*. The main input to the overall problem is the *waiting list* of each discipline, containing all the case surgeries that currently need to be performed. Besides the patient personal record, for each case surgery, the following information is specified in the waiting list:

- Surgery code – identifies the specific type of surgery.
- Processing time – expected duration of the surgery (including setup times due to cleaning and OR preparation for the next surgery). We assume all these times to be deterministic.
- Decision date – date when the surgery enters the waiting list, based on physician's prescription.
- Waiting time – days currently elapsed since the decision date.
- Priority class – surgeries are classified in three priority classes A, B or C (A having the highest priority), according to the regulatory essential assistance levels. As dictated by regional policies for waiting list management, this is a static classification which only depends on surgery type, not on the current waiting time.
- Due date – date within which the surgery should be performed. It is obtained by adding a quantity W to the decision date. W represents a maximum waiting time, and it only depends on the priority class.

Elective surgeries are not performed on Saturday and Sunday, therefore weekly schedules span five days. OR sessions are of three types, lasting either half a day (*morning* and *afternoon* sessions) or the whole day (*full-day* session). During one day, an OR can be either assigned one morning session and one afternoon session, or a single full-day session. All sessions of the same type have the same duration, which must not be exceeded by the total processing time of the surgeries allocated to that session.

In general, a MSS may be subject to various types of restrictions:

- *Discipline-to-OR restrictions.* Certain disciplines can only be performed in a restricted set of ORs, due to size and/or equipment constraints.
- *Limits on discipline parallelism.* Typically, no more than k OR sessions of a certain discipline can take place at the same time, e.g. because only k surgical teams for that discipline are available.
- *OR sessions-per-discipline restrictions.* Lower and upper limits on the number of OR sessions assigned to each discipline throughout one week can be specified. These restrictions may arise from workload balancing goals as well as from considerations on the number of available beds in the various wards.
- *OR reservation.* The hospital management may decide that there must be one or more OR sessions reserved for certain disciplines every day. (Note that this can also be used to reserve OR sessions to non-elective surgeries.)

The main management objectives are:

- Maximize the utilization of ORs, without resorting to overtime;
- As far as possible, perform each case surgery within the respective due date.

Hence, we define an objective function (to be maximized) that accounts for both these aspects. Namely, we associate a *score* to each surgery given by the product of the surgery processing time and a coefficient which depends on the current surgery waiting time.

In what follows, we introduce three one-week decision models. In all cases, the outputs of the model are the MSS and the SCA for next week.

- *Fixed model.* Given the MSS, the model computes the surgical case assignment (i.e., solves SCAP only).
- *Bounded-distance model.* Given a reference MSS, the model solves MSSP and SCAP concurrently, returning an MSS having limited distance from the reference MSS.
- *Flexible model.* MSSP and SCAP are solved concurrently and "from scratch", i.e., with no restrictions on the structure of the MSS.

In the next section, we illustrate in detail the three decision problems.

3. Formulations

3.1. Notation

S the set of surgical disciplines (indexed by s)

I_s the set of surgeries (indexed by i) in the current waiting list of the surgical discipline s

N_{OT} the total number of sessions available for planning in one week in the operating theater

J the set of operating rooms, indexed by j

z index for OR session type, $z \in \{m, a, d\}$, where m, a and d stand for morning, afternoon and full-day

w index for weekday, $w \in \{1, \ldots, 5\}$, from Monday ($w = 1$) to Friday ($w = 5$)

S_s^{min} minimum number of OR sessions to be allocated to the surgical discipline s in one week

S_s^{max} maximum number of OR sessions to be allocated to the surgical discipline s in one week

P_{is} expected duration of the i-th surgery of discipline s

W_A (W_B, W_C) maximum allowed waiting time for a surgery of class A (B, C)

R_{is} *slack time*, i.e., days to due date of the i-th surgery of discipline s (possibly negative for late surgeries)

PS_s maximum number of parallel sessions assigned to discipline s, $s = 1, \ldots, |S|$

O_z^{max} length (time) of a session of type z, $z \in \{m, a, d\}$

NA_s set of operating rooms not available for discipline s

γ_{sm} number of morning sessions reserved to discipline s

γ_{sa} number of afternoon sessions reserved to discipline s

Δ maximum allowed distance from a reference MSS.

3.2. Flexible model

Given the current state of each discipline waiting list, this problem consists in determining a complete plan, i.e., a MSS and a SCA. For the i-th surgery of discipline s, we define a *score* as $K_{is} = P_{is}(W_C - R_{is})$. In this way, priority among classes is enforced, and surgeries having small slack times are favored. The term P_{is} prevents from only selecting short surgeries.

We next present a mathematical programming formulation of the problem, using two families of binary decision variables:

x_{isjwz} $= 1$ if the i-th surgery of surgical discipline s is assigned to OR j for the day w in a session of type z.

y_{sjwz} $= 1$ if the surgical discipline s is assigned to OR j the day w in the session type z.

Notice that variables y_{sjwz} define the MSS, while the variables x_{isjwz} define the SCA. The mathematical formulation is:

$$
\begin{aligned}
\max \quad & \sum_s \sum_i \sum_j \sum_w \sum_z K_{is} \cdot x_{isjwz} && && (1)\\
\sum_j \sum_w \sum_z x_{isjwz} &\leq 1 \quad \forall i, s && && (2)\\
\sum_i P_{is} \cdot x_{isjwz} &\leq O_z^{max} \cdot y_{sjwz} \quad \forall s, j, w, z && && (3)\\
\sum_w \sum_j (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) &\geq S_s^{min} \quad \forall s && && (4)\\
\sum_w \sum_j (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) &\leq S_s^{max} \quad \forall s && && (5)\\
\sum_s (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) &\leq 2 \quad \forall w, j && && (6)\\
\sum_s y_{sjwz} &\leq 1 \quad \forall w, j, z \neq d && && (7)\\
\sum_j (y_{sjwm} + y_{sjwd}) &\geq \gamma_{sm} \quad \forall w, s && && (8)\\
\sum_j (y_{sjwa} + y_{sjwd}) &\geq \gamma_{sa} \quad \forall w, s && && (9)\\
\sum_j (y_{sjwm} + y_{sjwd}) &\leq PS_s \quad \forall w, s && && (10)\\
\sum_j (y_{sjwa} + y_{sjwd}) &\leq PS_s \quad \forall w, s && && (11)\\
\sum_w \sum_z \sum_{j \in NA_s} y_{sjwz} &= 0 \quad \forall s && && (12)\\
x_{isjwz} &\in \{0, 1\} \quad \forall i, s, j, w, z && && (13)\\
y_{sjwz} &\in \{0, 1\} \quad \forall s, j, w, z && && (14)
\end{aligned}
$$

Constraint (2) states that each surgery can be performed at most once. Constraint (3) establishes an upper limit to the duration of the surgical cases assigned to the same session. Constraints (4) and (5) bound the number of weekly OR sessions assigned to each discipline. Observe that one full-day session type counts as two half-day (either morning or afternoon) session types. Constraints (6) and (7) together guarantee that there are no two surgical disciplines assigned to the same OR at the same time. More specifically, constraint (6) imposes that either a single full-day session or two half-day sessions are assigned to the same OR in the same day, whereas constraint (7) implies that, in the case of at most two half-day sessions, these are one morning and one afternoon session. Constraints (8) and (9) enforce OR reservation. Note that in order to have at least γ_{sm} (γ_{sa}) ORs assigned to discipline s every morning (afternoon), we can use both morning sessions (afternoon sessions) or full-day sessions. Constraints (10) and (11) limit the number of parallel sessions assigned to the same surgical discipline. Finally, discipline-to-OR restrictions are taken into account by constraint (12).

3.3. Bounded-distance model

This model takes as input, besides the current state of each discipline waiting list, also a *reference MSS*. As in the previous problem, the solution specifies a complete plan, i.e., a MSS and a SCA. However, the distance of the MSS from the reference MSS cannot exceed Δ.

We describe the reference MSS by means of the triple sets M_R, A_R and D_R. More specifically, if $(s, j, w) \in M_R$, OR j is assigned discipline s in a morning session of day w in the reference MSS. (A similar meaning holds for A_R and D_R for afternoon and full-day sessions.) We let N_{OT} denote the total number of sessions available in the OT during the week, and Δ the maximum allowed distance from the reference MSS.

Observe that, in the reference MSS, there can be a full-day session assigned to a given surgical discipline s_1. Then if, in the computed MSS, the full-day session is split into a morning session assigned to s_1 and an afternoon session assigned to a different discipline s_2, the contribution to the distance between the two MSSs should count as 1. If the full-day session assigned to discipline s_1 in the reference MSS is now assigned to a different discipline s_2, the contribution to the distance between the two MSSs is 2. Therefore, the Bounded-distance model can be formulated adding to (1)–(14) the constraint:

$$\sum_{(s,j,w)\in M_R} y_{sjwm} + \sum_{(s,j,w)\in A_R} y_{sjwa} + \sum_{(s,j,w)\in D_R} (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) \geq N_{OT} - \Delta \tag{15}$$

In fact, the left-hand side of (15) accounts for all the sessions that are assigned to the same surgical discipline as in the reference MSS, for each operating room and each day. The right-hand side defines the minimum number of unchanged sessions.

3.4. Fixed model

In the fixed model, the MSS is given. Therefore, the only decision left is the assignment of surgeries to the OR sessions allocated to each surgical discipline. In other words, this model solves SCAP only. Let Q_s be the number of OR sessions assigned to surgical discipline s in the given MSS, and O_{hs}^{max} the duration of the h-th such session, $h = 1, \ldots, Q_s$. Here we let $x_{ish} = 1$ if the i-th surgery of discipline s is assigned to the h-th OR session of discipline s, otherwise $x_{ish} = 0$.

The objective function is the same as in the previous models. Therefore, the mathematical formulation is the following:

$$\max \quad \sum_s \sum_h \sum_i K_{is} \cdot x_{ish} \tag{16}$$

$$\sum_h x_{ish} \leq 1 \quad \forall i, s \tag{17}$$

$$\sum_i P_{is} \cdot x_{ish} \leq O_{hs}^{max} \quad \forall s, h \tag{18}$$

$$x_{ish} \in \{0, 1\} \quad \forall i, s, h \tag{19}$$

Observe that the Fixed model decomposes into several bin-packing-type problems, one for each surgical discipline, in which surgeries correspond to items and sessions to bins.

4. Case study and computational results

In this section we discuss the computational experiments set up for the OT of a medium-size public hospital. In Section 4.1 we present the details on the case study, and in Section 4.2 we illustrate the numerical results obtained.

4.1. Case study

We first describe the application scenario (Section 4.1.1). In Section 4.1.2, the planning policies and the performance indices designed to evaluate them in the specific case study are described. Detailed information on the settings used in the computational experiments is given in Section 4.1.3.

4.1.1. Application scenario and model implications

The San Giuseppe hospital is a public general hospital located in Empoli, Tuscany (Italy). With its almost 500.000 square feet and over 400 beds, San Giuseppe is medium-sized among Italian public hospitals. Recently, the hospital significantly increased its physical size, which led to starting a major revision of its processes, also favored by the regional government policy. In this context, the hospital managers wanted to evaluate the effectiveness of their current MSS planning policy against alternative solutions, from the viewpoint of OR utilization and due date performance.

In the operating theater, there are $|J| = 6$ operating rooms devoted to elective surgery. These rooms are all identically equipped, but two of them ($j = 5, 6$) are larger than the others.

Surgeries belong to the following disciplines: general surgery (GS), otolaryngology, referred to as ear-nose-throat surgery (ENT), gynecology (GYN), orthopedic surgery (ORTH), and urology (URO). Moreover, for modeling purposes and upon OT managers' suggestion, we consider day surgery (DS) as a discipline by itself, since it consists of short surgeries only, that can be managed more effectively if accounted for separately from the other disciplines. Thus, the set of surgical disciplines is $S = \{\text{GS}, \text{ENT}, \text{GYN}, \text{ORTH}, \text{URO}, \text{DS}\}$. Table 1 shows relevant data concerning restrictions on room assignments (specifically, GYN must be always performed in room 1 and ORTH in the largest rooms 5 and 6), maximum number of parallel sessions assigned to the same discipline, and upper and lower limits on the number of sessions assigned to each discipline throughout the week.

Table 1: Restrictions on MSS for case study.

discipline	NA_s	PS_s	$S_s^{\min}$	$S_s^{\max}$
GS	-	2	8	20
ENT	-	1	3	10
GYN	2,3,4,5,6	1	6	10
ORTH	1,2,3,4	2	15	20
URO	-	1	3	10
DS	-	1	8	10

The surgery plan (spanning from Monday to Friday) is prepared one week ahead, on Monday. All sessions are divided into time units of 15 minutes each. A morning session lasts 26 time units, an afternoon session 20 time units, and a full-day session 46 time units. However, we use smaller values for the capacity of the above sessions, in order to leave a planned slack time for possible delays and/or uncertainties affecting surgery duration. Therefore, in our planning models (Sections 3.2-3.3) we have $O_m^{max} = 24$, $O_a^{max} = 18$, and $O_d^{max} = 42$, respectively.

The OT of the hospital has one operating room fully dedicated to emergencies (and therefore not included in set J). Furthermore, to face two possible emergencies at the same time, OT managers decided that every morning one OR of J must be always made available in a short time, and every afternoon one operating room must always remain free. The morning requirement is achieved by assigning a morning session to day surgery (whose cases are relatively short) every day. This is modeled through constraint (8), letting $\gamma_{sm} = 1$ for $s =$ DS, and replacing the inequality with an equality. To reserve one OR to emergencies every afternoon, the following constraints (20) are added to both the Flexible and the Bounded-distance models.

$$\sum_{s} \sum_{j} (y_{sjwa} + y_{sjwd}) \leq |J| - 1 \quad \forall w \,. \tag{20}$$

In conclusion, the total number of OR sessions available for elective surgery in one week is $N_{OT} = 2$ (OR sessions/day) $\cdot 5$ (days/week) $\cdot 6$ (ORs) $- 5$ (OR sessions reserved to non-elective surgery) $= 55$, while the total number of time units available every week is given by 42 (units $\cdot$ OR/day) $\cdot$ 6 (ORs) $\cdot$ 5 (days)-$18 \cdot 5$ (the OR sessions reserved to non-elective surgery) = 1170.

We were provided with the current waiting lists for all the six surgical disciplines in S. The case surgeries are grouped into three priority classes A, B and

C having a nominal maximum allowed waiting time $W_A = 30$, $W_B = 60$ and $W_C = 90$ days respectively, according to what enforced by regional regulations.

4.1.2. Planning policies and performance indices

Our experiments focus on testing and comparing various alternative MSS change policies (Section 2) over a one-year horizon. For each week inside a block, the Fixed model is solved. Whenever changes are allowed, an instance of the Bounded-distance model (or the Flexible model, if $\Delta = \infty$) is solved.

After an in-depth discussion with the OT managers, a number of change policies have been proposed for evaluation:

- $(52, 0)$ – keep the given MSS throughout the year (*stable policy*)
- $D(4, 2)$ – allow two changes at the end of a 4-week period
- $D(1, 1)$ – allow one change every week
- $D(13, \infty)$ – keep the same MSS for three months, then devise a brand new one
- $D(1, \infty)$ – change MSS every week, with no constraints (*flexible policy*)
- $S(1, 1)$ – every week, allow one change with respect to a given reference MSS

These combinations of b and Δ have been selected (along with the OT managers) to cover a wide range of sensible MSS management policies, each providing a different tradeoff between MSS flexibility and stability. In particular, (52,0) is the policy currently in use in the hospital San Giuseppe, while $D(13, \infty)$ and $S(1, 1)$ apparently represent other common approaches in medium-size hospitals in Tuscany.

To evaluate the performance of the system under the proposed planning policies, we analyze average statistics over 52 weeks. More specifically, we focus on the following indicators, computed every week:

(*i*) ♯ cases: number of surgical cases scheduled in the week;

(*ii*) % of *empty* time units over the total number of time units available, namely:

  a. time units not assigned to any surgery,

  b. time units not assigned to a surgical discipline because the corresponding waiting list is empty;

(*iii*) ♯ late cases: number of overdue surgical cases scheduled in the week;

(*iv*) mean lateness: sample mean of the lateness (days) of all surgical cases scheduled in one week, where the lateness of a surgical case is the difference between the time when the case surgery is performed and its due date;

(*v*) max lateness: maximum lateness (days) among all surgical cases scheduled in the week;

Table 2: Cardinality of the surgery waiting lists at the beginning of the simulation and parameters of the arrival distribution in the three experimental scenarios.

s	base			stressed	large-scale		
	$\|I_s\|$	min_s	max_s	$\|I_s\|$	$\|I_s\|$	min_s	max_s
GS	230	23	40	330	345	46	80
GYN	244	25	43	244	366	50	86
ORTH	429	44	75	429	643	88	150
URO	112	12	20	112	168	24	40
ENT	101	10	17	101	150	20	34
DS	257	26	45	357	385	52	90

(*vi*) mean tardiness: sample mean of the tardiness (days) of all surgical cases scheduled in the week, where the tardiness coincides with the lateness, if the surgical case is late, otherwise it is zero;

(*vii*) waiting time: waiting time (days) averaged over all surgical cases scheduled in the week.

These indicators account for the main goals of surgical scheduling such as effective and efficient use of operating rooms (*i–ii*), delay reduction (*iii–vi*, patients' safety and satisfaction (*vii*).

Furthermore, for each policy we compare the status of the waiting lists at the beginning and at the end of the simulated period (i.e. 52 weeks). To this aim, we consider the total number of cases in the waiting lists and their average current waiting time.

4.1.3. Experimental design and setting

In our computational experiments, we solve the MSS and SCA problems week by week, assuming that all weeks are identical, i.e., we do not account for midweek holidays or any other break.

Our experimental campaign tested the six change policies in three distinct scenarios, we will refer to as *base*, *stressed* and *large-scale*. In each scenario, we simulated the system and evaluated its performance under alternative planning policies for 10 realizations of a 1-year period. Throughout the simulation of one year, we update the waiting lists every week, deleting all surgeries that have been performed during the current week and accounting for new surgery arrivals.

For the *base scenario*, the input of the first week consists of the current waiting lists provided by the hospital (Table 2). For each surgical discipline s, there is a random number of arrivals each week, sampled from a distribution estimated by OT managers, namely, a uniform distribution $U_s^{base}[min_s, max_s]$ centered around the average weekly arrival rate. These data are reported in Table 2. Note that, even if the literature reports cases of seasonal variation for some specific surgical services (e.g., see Upshur et al. [17]), the OT managers consider the arrivals grouped by surgical discipline, not by surgical case.

Table 3: MSS adopted in the Fixed Model.

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<tr><th></th><th colspan="2">Monday</th><th colspan="2">Tuesday</th><th colspan="2">Wednesday</th><th colspan="2">Thursday</th><th colspan="2">Friday</th></tr>
<tr><td>$j = 1$</td><td>GYN</td><td>empty</td><td colspan="2">GYN</td><td colspan="2">GYN</td><td>GYN</td><td>URO</td><td colspan="2">GYN</td></tr>
<tr><td>$j = 2$</td><td colspan="2">DS</td><td>ENT</td><td>empty</td><td colspan="2">DS</td><td colspan="2">DS</td><td colspan="2">DS</td></tr>
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<tr><td>$j = 6$</td><td colspan="2">ORTH</td><td colspan="2">ORTH</td><td>ORTH</td><td>empty</td><td colspan="2">ORTH</td><td>ORTH</td><td>empty</td></tr>
</table>

Hence, seasonality of a specific case is not so relevant in the planning/scheduling context. Also, OT managers report that while seasonality does occur for non-elective surgery, it is much less significant for elective surgery. For the policy $(52, 0)$ (stable policy), we use the MSS currently adopted in the hospital, which is shown in Table 3. We also use it as reference MSS in policy $S(1, 1)$.

The *stressed scenario* is aimed at simulating the behavior of the system starting from a congested condition. This scenario may represent the effect of different possible causes, such as an occasionally high rate of non-elective surgery, unpredicted demand variability, seasonality in surgical arrivals and/or in the resources availability. The purpose is to compare the ability of different long-term policies to recover from congestion. The hospital management reports that such problems are more likely to occur for DS and GS. Hence, we add 100 surgeries to the values of I_{GS} and I_{DS} in the base scenario, representing about 40% of $|I_s|$ for $s = \text{GS}, \text{DS}$, and almost 15% of the total number of cases in the waiting lists. All these additional surgeries are assumed to be $2W_C = 180$ days late.

To enable a fair comparison among these first two scenarios, in the stressed scenario the same 10 realizations of 1-year arrivals generated for the base scenario have been used. Also in this scenario, in the policies $(52, 0)$ and $S(1, 1)$ we use the MSS currently adopted in the hospital (Table 3). In both base and stressed scenarios, the maximum computation time to solve an instance of the Flexible model or of the Bounded-distance model was set to 5 minutes. The time limit for the Fixed model has been set to 1 minute. On the basis of the results of preliminary tests, these time limits have been observed to yield a satisfactory trade-off between computation time and solution quality (the gap is always less than 1% at the time limit).

In order to validate the policies in a larger setting, we have run experiments on a different scenario, characterized by 12 operating rooms instead of 6. In such *large-scale scenario*, we considered double initial waiting lists and arrival rates for each discipline with respect to the base scenario (see the parameters min_s, max_s in Table 2). Similarly, all parameters concerning restrictions on MSS (Table 1) have also been doubled, in order to describe a setting having the same features of the base scenario but twice the size. However, the amount of flexibility provided by the various change policies has *not* been doubled, thus allowing a finer evaluation of the impact of flexibility than in the base

Table 4: Weekly average performance of planning policies in the base scenario.

	♯ cases	♯ late cases	% empty t.u.	% empty t.u.*	mean lateness	max lateness	mean tardiness	waiting time
(52,0)	186	69	4.51%	4.45%	-7	49	12	66
D(13,∞)	192	63	0.99%	0.72%	-10	31	9	63
D(4,2)	194	50	0.10%	0.02%	-12	31	8	62
D(1,1)	194	43	0.05%	0.00%	-11	22	7	63
D(1,∞)	193	30	0.04%	0.00%	-17	13	7	57
S(1,1)	189	60	3.13%	3.08%	-10	37	10	64

scenario. In the large-scale scenario, the time limits have been set to 10 minutes for Flexible and Bounded-distance models and 3 minutes for the Fixed model. Also in this case, these time limits have been established on the basis of the observation of preliminary tests.

All tests have been performed on a AMD Athlon(tm) 64 X2 Dual Core Processor 5000+, 2,60 GHz processor with 2 GB of RAM, using OPL Studio 6.1 and the CPLEX 11.2 MILP solver for the mathematical programming models. In our experiments, symmetry-breaking constraints have been added to the mathematical programming models in Section 2, having the sole purpose of efficiently restricting the set of feasible solutions, thus reducing the computational burden.

4.2. Numerical results

We now discuss the performance of the proposed planning policies, evaluated through the indices presented in Section 4.1.2, averaged over 52 weeks and 10 repetitions of each policy. These results are organized in tables in which each row corresponds to a policy and the columns refer to the performance indices. Tables 4, 7 and 12 refer to the base, stressed and large-scale scenarios respectively. Then, we report the comparison of the status of the waiting lists at the beginning and at the end of the simulated period. We do this for the three scenarios in Tables 5, 8 and 13. A detailed analysis by priority classes is given in Tables 6 and 9–11.

4.2.1. Base scenario

Table 4 reports the results for the base scenario. Columns 1 and 2 show the total number of surgeries (throughput) and the number of late surgeries performed per week, respectively. Column 3 reports the percentage of empty time units, i.e., time units in which an OR is not in use. Column 4 shows the percentage of empty time units due to empty waiting lists. This may happen when a discipline has an empty waiting list but an assigned OR session. The empty time units in column 3 (%empty time units) include those in column 4 (%empty time units*). Finally, the values reported in columns 5–8 refer to the surgeries performed during one week and are measured in days. Table 5 reports information on the surgeries in the initial waiting lists (first row) and those remaining in the final (after one year) waiting lists produced by each policy (following rows) in the base scenario. The comparison is done aggregating all disciplines. Table 6 shows a breakdown of such comparison by priority class. A few comments are in order.

- As for the percentage of empty time units, the stable policy is the least efficient. Among the other policies, all dynamic policies outperform $S(1, 1)$. Note that the inferior performance of the stable policy is essentially due to empty waiting lists (column 4). In fact, keeping the MSS fixed, if one or more waiting lists are currently empty, the corresponding OR sessions remain empty as well and cannot be assigned to other disciplines. Such a behavior also explains the reason for scheduling (on average) less surgical cases than the other policies (column 1). However, even with the stable policy, if we do *not* consider OR sessions which are empty because of empty waiting lists, we can observe that the Fixed model allows to fill OR sessions almost perfectly.

- The best policies are $D(1, 1)$, $D(4, 2)$ and $D(1, \infty)$. Somewhat surprisingly, the performances of these policies are extremely close. This suggests that the introduction of an even small amount of flexibility allows the reference MSS to evolve according to the arrival process. These policies allow to significantly cut figures such as the average number of late cases and maximum lateness with respect to $(52, 0)$. Keeping the MSS fixed for a long time is not the best choice, as also confirmed by $D(4, 2)$ being slightly worse than $D(1, 1)$.

- In terms of all due date performance indices, the stable policy is the worst. This is also apparent from the final state of the waiting lists (Table 5, recall that tardiness values are averaged over *all* cases in the list, not only tardy cases). Actually, $D(13, \infty)$ and $S(1, 1)$ are better than $(52, 0)$ but they are outperformed by the other dynamic policies. These considerations suggest that keeping the MSS constant for a long time is not paid off by having large flexibility among two blocks, as well as keeping the same reference MSS is not particularly profitable if the actual MSS is closely bound to it.

- Actually, to support the choice of the planning policy to be implemented in the OT, it is relevant to compute the actual distance between the MSSs of two consecutive weeks according to the various change policies. We observed that, when using $D(1, \infty)$, the weekly average distance between two consecutive MSSs is 12.5. Throughout the year, the distance between two consecutive MSSs varied between 5 and 37. Being $N_{OT} = 55$ (Section 4.1.1), this means that on average the Flexible model changes $12.5/55 \cdot 100 = 20\%$ of the whole MSS every week, with a maximum of $37/55 \cdot 100 = 67\%$. Note that $D(1, 1)$ and $D(4, 2)$ provide a much higher stability, by changing on average less than $2/55 \cdot 100 \approx 4\%$ of the whole MSS.

- Comparing initial and final waiting lists, we observe that with the stable policy the final size of the waiting list is larger than the initial size, even if all the other indicators improve with respect to their initial value. All

Table 5: Comparison between initial and final waiting list for each planning policy in the base scenario

	♯ cases	♯ late cases	mean lateness	max lateness	mean tardiness	waiting time
Initial situation	1373	777	16	180	33	90
(52,0)	1500	246	-31	47	3	44
D(13,∞)	1159	13	-46	-1	0	34
D(4,2)	1049	9	-50	-4	0	30
D(1,1)	1057	2	-53	-11	0	28
D(1,∞)	1066	0	-53	-13	0	21
S(1,1)	1327	117	-37	23	1	40

Table 6: Comparison between initial and final waiting lists by priority class in base scenario

	Priority class A		Priority class B		Priority class C	
	♯ cases	waiting time	♯ cases	waiting time	♯ cases	waiting time
Initial situation	157	55	413	78	803	103
(52,0)	108	29	538	46	854	44
D(13,∞)	46	13	314	28	799	36
D(4,2)	30	9	266	23	757	31
D(1,1)	29	9	252	22	776	30
D(1,∞)	27	9	258	21	781	31
S(1,1)	82	21	441	38	804	42

dynamic policies produce very few remaining late cases in the final lists. In this respect, the static policy appears inferior (though still better than $(52, 0)$), perhaps due to a suboptimal choice of the reference MSS.

- From Table 6, we observe that *all* the proposed policies show a fair management of the three priority classes. In particular, while class A surgeries are 11.4% in the initial waiting lists, they reduce to 7.2% in the final waiting lists for the stable policy, 6.2% for $S(1, 1)$, 3.9% for $D(13, \infty)$ and less than 3% for the other policies.

4.2.2. Stressed scenario

Table 7 shows the performance of the proposed planning policies in the stressed scenario. The results are similar to those observed in Table 4, although indicators in columns 5–8 take higher values than in the base scenario. Again, $(52, 0)$ appears as the worst performing policy, while the other policies perform reasonably well also in the stressed scenario.

Also the comparison between initial and final waiting lists (Tables 8 and 9) confirms the results observed in the base scenario, with an expected worsening of almost all indicators due to the congested situation.

Table 7: Weekly average performance of planning policies in the stressed scenario.

	♯ cases	♯ late cases	% empty t.u.	% empty t.u.*	mean lateness	max lateness	mean tardiness	waiting time
(52,0)	187	91	4.26%	3.77%	2	67	19	76
D(13,∞)	191	89	0.75%	0.59%	2	49	15	75
D(4,2)	193	61	0.04%	0.00%	1	45	14	74
D(1,1)	193	55	0.03%	0.00%	1	40	13	74
D(1,∞)	193	44	0.03%	0.00%	-5	27	12	69
S(1,1)	190	84	2.09%	2.01%	0	56	16	73

Table 8: Comparison between initial and final waiting list for each planning policy in the stressed scenario

	♯ cases	♯ late cases	mean lateness	max lateness	mean tardiness	waiting time
Initial situation	1573	905	-36	180	57	119
(52,0)	1651	363	-27	51	4	48
D(13,∞)	1402	24	-44	13	0	35
D(4,2)	1289	17	-47	1	0	32
D(1,1)	1272	8	-48	-4	0	32
D(1,∞)	1269	1	-49	-8	0	25
S(1,1)	1444	174	-34	31	2	42

Table 9: Comparison between initial and final waiting lists by priority class in stressed scenario

	Priority class A		Priority class B		Priority class C	
	♯ cases	waiting time	♯ cases	waiting time	♯ cases	waiting time
Initial situation	162	59	452	92	959	130
(52,0)	122	32	580	48	949	50
D(13,∞)	58	15	361	29	983	38
D(4,2)	30	13	278	28	981	33
D(1,1)	29	11	252	25	991	34
D(1,∞)	27	10	259	24	983	34
S(1,1)	94	25	493	41	857	44

Table 10: Comparison between priority class in stressed scenario for GS

	Priority class A		Priority class B		Priority class C	
	♯ cases	waiting time	♯ cases	waiting time	♯ cases	waiting time
initial situation	31	95	75	158	224	180
(52,0)	1	32	76	41	335	60
D(13,∞)	1	7	23	16	167	33
D(4,2)	1	8	35	21	202	38
D(1,1)	1	8	37	22	202	38
D(1,∞)	2	7	33	20	198	36
S(1,1)	1	18	57	31	266	48

Table 11: Comparison between priority class in stressed scenario for DS

	Priority class A		Priority class B		Priority class C	
	♯ cases	waiting time	♯ cases	waiting time	♯ cases	waiting time
initial situation	3	52	51	141	303	174
(52,0)	1	7	6	7	29	7
D(13,∞)	1	7	6	7	165	24
D(4,2)	1	7	7	8	151	23
D(1,1)	1	7	7	8	176	25
D(1,∞)	0	0	11	9	180	25
S(1,1)	1	7	6	7	29	7

For the stressed scenario we perform a more detailed analysis of the final waiting lists for the two "critical" disciplines, namely GS and DS. The results in Tables 10 and 11 show that even for DS and GS, the stable policy provides the worst performances in terms of average waiting time and list size at the end of the simulation. When comparing the final size of the waiting lists for the various policies, we must consider that while most cases in day surgery belong to class C, cases in general surgery are more balanced among the three classes. As a consequence, change policies tend to favor GS with respect to other disciplines, such as DS, so that the total number of OR sessions devoted to DS over one year is lower with dynamic policies. In fact, in the stressed scenario, the (fixed) MSS currently used in the hospital still allows to be at pace with the demand of day surgeries, but appears dramatically undersized for general surgery. These results suggest once more that a change policy can be very useful, but its parameters b and Δ must appropriately reflect management goals and constraints.

For the stressed scenario we analyze the ability of the system to recover from the initial stress situation. For this purpose we consider the policies $(52, 0)$, $D(4, 2)$, $D(1, 1)$ and $D(1, \infty)$. Figure 1 shows the average values of lateness and number of late cases in the waiting lists at the end of each week.

The two graphs show that the best policies require 7 to 9 weeks to recover from the stress condition. However, we note that after an initial acceptably fast recovery, $(52, 0)$ significantly deviates from the behavior of other policies. Once more, the stable policy underperforms, especially in the last weeks of the observed period. This is even more apparent in terms of number of late cases.

Actually, the initial fast recovery is due to the structure of the MSS as defined by the hospital management, which has many OR sessions devoted to DS and GS (see Table 3, recall that in the stressed scenario we created a backlog on DS and GS). However, in the long run keeping the MSS fixed over time negatively affects the performance of the other disciplines, and hence of the overall behavior of the policy. In fact, the final trend of the $(52, 0)$ line (Figure 1) is slowly but continuously increasing. Such trend is caused by the increase in the number of surgeries with respect to the beginning of the year. In the first weeks, the exact solution to SCAP allows a relevant improvement of the initial situation. However, particularly in this stressed scenario, in the long run the fixed MSS is not capable to effectively follow the evolution of the lists, despite a significant decrease in the transient period.

This shows that the joint effect of an accurate solution of SCAP and of a suitable change policy can be highly beneficial for waiting list management. We retrieve a similar result in the next section. In the figure, we note that while $D(1, \infty)$ is the best policy, even $D(4, 2)$ is flexible enough to produce a sustainable behavior in the long run.

4.2.3. Large-scale scenario

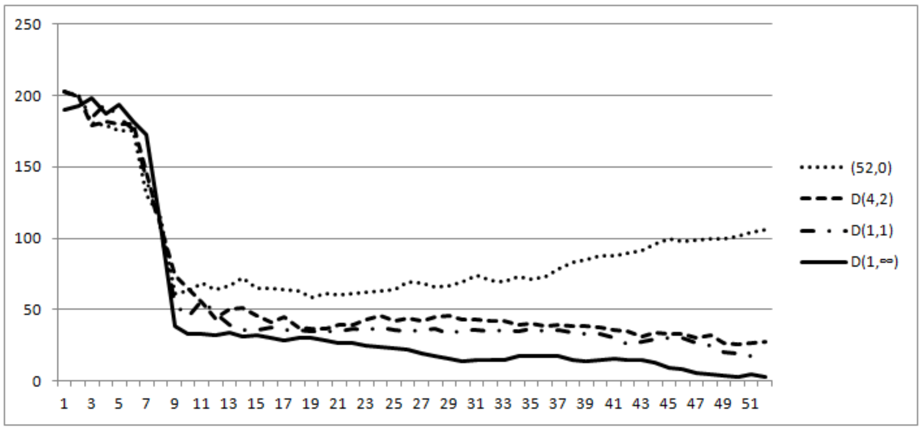
In the large-scale scenario, similar considerations to those for the base scenario hold concerning the relative behavior of the various policies. This suggests that the model is scalable and easily adaptable to larger OTs.

Based on Table 12, we observe that the stable policy is clearly dominated by the other policies in terms of OR utilization, while its throughput is comparable with $S(1, 1)$. This is not surprising, since in this case $N_{OT} = 110$, and $S(1, 1)$ only allows a single change out of 110 available OR sessions. Overall, the due date performance of all policies remains almost comparable with that observed in the base scenario.

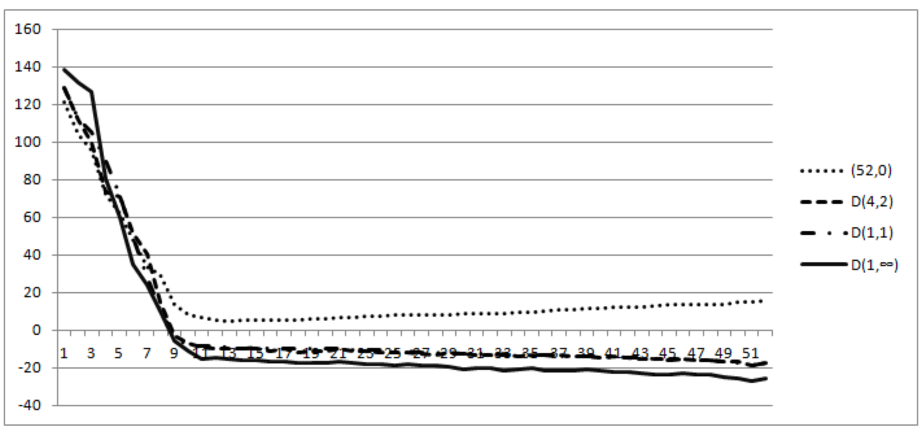
As already observed in Section 4.2.1, Table 13 suggests that all change policies provide shorter waiting lists at the end of the year as compared to the initial waiting list, thus confirming that even small but frequent changes in the MSS allow the policy to follow the evolution of the waiting lists. Notice that in the stable policy, even though the size of the final waiting list is larger than the initial size, all the other indices considerably improved.

5. Conclusions and future research

The main purpose of this study is to evaluate long-term policies in MSS planning. We focused in particular on the tradeoff between organizational complexity (stemming from the MSS changing over time) and effectiveness of the plan, as captured by a number of performance indices. The results of the experiments suggest that introducing even a limited amount of flexibility in the



(a) Mean Lateness



(b) Number of Late Cases

Figure 1: Analysis of the ability of the system to recover from the initial stress situation: average values of lateness and number of late cases in the waiting lists at the end of each week.

Table 12: Weekly average performances of planning policies in the large-scale scenario.

	♯ cases	♯ late cases	% empty t.u.	% empty t.u.*	mean lateness	max lateness	mean tardiness	waiting time
(52,0)	382	104	4.46%	4.42%	-13	42	10	59
D(13,∞)	386	97	0.50%	0.43%	-11	44	9	63
D(4,2)	387	91	0.04%	0.00%	-11	21	8	62
D(1,1)	387	91	0.06%	0.00%	-11	21	8	62
D(1,∞)	387	78	0.07%	0.00%	-11	15	7	63
S(1,1)	380	118	1.89%	1.71%	-11	39	11	63

Table 13: Comparison between initial and final waiting list for each planning policy in the large-scale scenario

	♯ cases	♯ late cases	mean lateness	max lateness	mean tardiness	waiting time
Initial situation	2746	905	-36	180	57	119
(52,0)	2824	454	-33	26	2	44
D(13,∞)	2232	297	-40	48	4	39
D(4,2)	2134	7	-52	-9	0	29
D(1,1)	2127	12	-52	-9	0	29
D(1,∞)	2127	0	-53	-16	0	28
S(1,1)	2546	343	-35	32	2	40

structure of the MSS can yield significant benefits, in terms of average waiting time and due date performance. Also, small but frequent changes are better than large but infrequent changes. The parameters of the change policy may become an element of negotiation which can actually help personnel to become more involved in such planning system.

On the basis of our study, the hospital management of San Giuseppe is currently considering the introduction of such limited degree of flexibility in an experimental phase which is supposed to start in the next months.

From the viewpoint of the viability of the approach, we observe that computation times are sufficiently small to use the models to perform what-if analysis, or to recompute feasible plans in the face of unpredicted events. Also, in all our experiments with the stable policy we have always used the current MSS of the San Giuseppe hospital. Of course, analyzing long-term arrivals, one can devise alternative (fixed) MSSs, which might yield a better performance than the one currently employed by the hospital. This can be assessed by running one-year simulations, which points out another possible use of our models.

Future research may first address possible refinements and improvements of the models presented, such as including detailed surgeons' timetables in the planning phase and accounting for uncertainties (e.g. in surgical case durations). Also, future research should concern the integration of elective surgery planning with the other stages of the surgical path. In fact, related problems concern planning visit before surgery (pre-hospitalization), as well as allocation of beds in ICU and wards (bed management and discharge planning).

In this context, planning and scheduling models can be profitably used in a simulation-optimization scheme which enables to consider more relevant aspects of the healthcare systems under study, including uncertainties and stochastic variables. Potential benefits of this integrated approach may include better clinical results, higher patient and hospital staff satisfaction, improved patient safety and better financial performance for healthcare organizations.

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