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Long term evaluation of operating theater planning policies

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Abstract

This paper addresses the problem of Operating Room (OR) planning and scheduling. More specifically, we first focus on determining the Master Surgical Schedule (MSS) on a weekly basis, by assigning the different surgical disciplines to the available sessions. Next, we allocate surgeries to each session, focusing on elective patients only; patients 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 (OT) of a public hospital in Empoli, Italy. We set up a campaign of computational experiments aimed at investigating the performance of alternative policies for the management of the MSS and the waiting lists over a one-year time horizon.

Keywords: surgical planning, operating room scheduling, master surgical schedule, surgical sequencing

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 (surgical teams, equipment etc.); see Sobolev et al. (2006) [13] and Cerda et al. (2006) [3].

Several operating rooms (ORs), possibly with different characteristics, are managed in a single OT and may be shared among different surgical disciplines. In this study we are concerned with allocation of elective surgeries only. However, as described later, such allocation must also 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 often referred to as Master Surgical Schedule Problem (MSSP) [2], its output being the Master Surgical Schedule (MSS). Problem (ii) determines the Surgical Case Assignment (SCA) [16], and is therefore denoted as Surgical Case Assignment Problem (SCAP).

Problem (*iii*) outputs the detailed calendar of elective surgeries for each session; we refer to this problem as Elective Surgery Sequencing Problem (ESSP). Given the patients waiting list and various information on OT characteristics and status, these problems aim at optimizing several performance measures including operating rooms utilization, throughput, surgeons' overtime, lateness etc.

In the last years, operating room planning and scheduling problems have been studied by several researchers (e.g. [2, 7, 15, 12]), with the aim of providing the OT managers with an efficient surgery plan.

Testi et al. [14] use a three-phase approach to determine the MSS, the SCA and the detailed surgery sequencing. In their approach, they first estimate the number of weekly sessions for each discipline, then they compute the MSS, whereas in the third phase they use a discrete-event simulation model to schedule elective surgeries. Jebali et al. and Fei et al. [9, 6] present a two-phase approach for the scheduling of the operating rooms, which substantially correspond to SCAP and ESSP. For SCAP, Persson and Persson [11] propose a simulation-based approach and include several cost measures in a rolling horizon optimization model. Van Oostrum et al. [17] propose a two phase approach to construct the MSS minimizing the number of used operating rooms when the surgical cases are already decided and leveling the hospital bed requirements. Pham and Klinkert [10] address a surgical case scheduling problem (SCAP and ESSP) utilizing an extension of the job shop scheduling problem called multi-mode blocking job shop and present a mixed integer linear programming (MILP) formulation to minimize performance measures as the makespan or operating room overtime. Also Dexter and Traub [5] address the same problems when surgical cases are pre-decided and the problem is to assign them to ORs. They propose two rules based on Earliest Start Time and Latest Start Time, to maximize the efficiency of use of OR time. Sier et al. [12] tackle the surgical task scheduling problem with a simulated annealing technique. Van Houdenhoven et al. (2007) [18] apply portfolio optimization and bin packing models to schedule inpatient surgical cases. Denton et al. [4] formulate ESSP as a stochastic optimization model and propose some effective solution heuristics to calculate OR schedule under uncertainty. Given a single OR they show how a simple sequencing rule can reduce the patient waiting time, the operating room idling time and the makespan. Blake et al. [1] utilize an ILP model to allocate time blocks to surgical disciplines minimizing the gap between demands and actual time blocks assignment (MSSP). While Testi et al. [15] propose an ILP model for concurrently solving MSSP and SCAP. In a follow-up paper [16] a pre-assignment heuristic to reduce problem size is introduced.

Similar to [15, 16], in this paper we propose a set of mathematical programming models and simple heuristics for MSSP and SCAP. We aim to evaluate the effect of various MSS and SCA policies in the long term, simulating the system's behavior throughout one year. We observe that MSSP is a problem at the tactical level, while SCAP and ESSP belong to the operational level. In fact, in many hospitals the MSS problem is solved once every few months, during which the same MSS is employed. Another approach is to allow a totally different MSS every week. The latter policy expectedly results in better solutions for the SCA problem. However, this gain has to be traded off against increased organizational complexity. Hence, in this paper we propose modeling and algorithmic tools to better investigate and quantify this trade-off. Moreover, we also aim at characterizing the most appropriate approach from the viewpoint of the computational burden required. These evaluations are based on real data concerning a medium-size Italian hospital, located in Empoli (Tuscany).

The paper is organized as follows. In Section 2 the considered problem of OR planning is described in detail. In Section 3 the mathematical formulations and the algorithms are formally 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 problem of allocating elective surgeries to operating rooms over a given time horizon, e.g. one week. This covers the problems denoted as MSSP and SCAP. We now describe the distinctive features of the problems we deal with, inspired by the case study discussed in detail in Section 4; such problems do not explicitly account for surgeons and resources availability, pre- and post- operative care.

All elective surgeries are grouped into *surgical disciplines* (e.g., orthopaedics, day surgery). 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; i.e., they are not affected by uncertainty.
- Entrance time – date in which the surgery entered the waiting list.
- Waiting time – days currently elapsed since the entrance time.
- Priority class – surgeries are classified in three priority classes A, B or C (A being the most urgent), according to the regulatory essential assistance levels.
- Due date – nominal time within which the surgery should be performed. It is set on the basis of the entrance time and the priority class.

Elective surgeries are performed all days except Saturday and Sunday. For this reason, 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 (typically, for two different disciplines), or a single full-day session (hence, for a single discipline). 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 equipes for that discipline are available.
- *OR sessions-per-discipline restrictions.* Lower and upper limits to the number of OR sessions assigned to each discipline throughout one week can be specified; e.g., because of workload balancing or other management rules.

- *OR reservation*. The hospital management may reserve one or more OR sessions to certain disciplines every day. Note that this can also be used to enforce policies related to non-elective surgeries. For instance, viewing non-elective surgery as another surgical discipline, we can devote one afternoon session to it every day. Similarly, since day surgery involves only short surgeries, we may want to have a day surgery session each morning, so that the corresponding OR can be quickly made available if needed by an emergency.

The objectives of the overall management problem mainly concern:

- Maximizing the utilization of ORs, without resorting to overtime as far as possible;
- Performing each case surgery within the respective due date, limiting its waiting time.

In general, these two objectives may be partially conflicting. In fact, the former objective may lead to schedule surgeries that tightly fill OR sessions, but irrespective of the surgeries' due dates. On the other hand, scheduling surgeries based on their due date only may lead to inefficient utilization of ORs. Hence, we define an objective function (to be maximized) that allows to account 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 may depend either on the proximity to the surgery due date or on the surgery waiting time.

In this paper we address problems at the tactical (MSSP) and operational (SCAP) level. However, we propose three different one-week decision models, corresponding to different planning policies at the strategic level, that will then drive tactical and operational decisions. OT managers are typically interested in long-term planning *stability* and *flexibility*. The former aspect refers to personnel having a repetitive, predictable schedule, which is typically preferred since it allows a simpler scheduling of personal engagements. The latter concerns the ability to dynamically adapt the weekly plan to the evolution of the waiting list. Also these two aspects are potentially conflicting, since stability pushes towards having a constant MSS, while flexibility might benefit from changing the MSS over 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.

- *Unconstrained MSS*. The model solves MSSP and SCAP "from scratch", with no constraints on the MSS.
- *Constrained MSS*. Given a reference MSS, the model solves MSSP and SCAP, returning a MSS having limited deviation from the reference MSS.
- *Fixed MSS*. Given the MSS, the model computes the surgical case assignment (i.e., solves SCAP only).

In the next section, we illustrate in detail the mathematical formulation of these three decision models.

3 Formulations and algorithms

In what follows, we first introduce the notation (Section 3.1), and then we present the three optimization models proposed to solve MSSP and SCAP (Sections 3.2-3.4). In Section 3.5, we describe heuristics.

3.1 Notation

In the optimization models that follow, we denote by S the set of surgical disciplines (indexed by s), and by I_s the set of surgeries (indexed by i) in the waiting list of the surgical discipline s. Let N_s denote the cardinality of I_s, i.e., the number of surgeries in the waiting list of the surgical discipline s. Let J denote the set of operating rooms, indexed by j. We identify the OR session type by $z \in \{m, a, d\}$, where m, a and d stand for morning, afternoon and full-day respectively. Weekdays are indexed by $w \in \{1, \dots, 5\}$, from Monday ($w = 1$) to Friday ($w = 5$). Moreover, we let:

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;

t_{is} entrance time of the i-th surgery of discipline s;

P_{is} expected processing time of the i-th surgery of discipline s;

T_{is} waiting time (days) of the i-th surgery of discipline s, i.e., time elapsed since t_{is};

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

c_{is} priority class of the i-th surgery of discipline s;

D_{is} due date of the i-th surgery of discipline s, computed as follows:

$$D_{is} = t_{is} + W_{c_{is}}\,; \tag{1}$$

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

$S_p^{(k)}$ set of disciplines that cannot be assigned to more than k parallel sessions, $k = 1, \dots, |J|$;

O_z^{max} time available for surgeries (*capacity*) 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.

3.2 Unconstrained MSS model

Given the current state of each discipline waiting list, this model outputs a complete plan, i.e., it determines a MSS and a SCA simultaneously.

The objective function of the model aims at maximizing the weekly ORs utilization, in terms of case surgeries duration (P_{is}), multiplied by a *score* K_{is}. Such score accounts for the case surgeries waiting time, and we propose two alternative definitions:

- Score 1. The score is the product of the case surgery waiting time T_{is} and a weight coefficient π_{is} depending on the priority class it belongs to (the higher the priority, the higher π_{is}), so that $K_{is} = T_{is}\pi_{is}$. This is similar to what done by [16].

- Score 2. The score is the difference between the waiting time associated to the lowest priority class (W_C) and the slack time R_{is}, i.e., $K_{is} = W_C - R_{is}$. Note that if $c_{is} = C$, K_{is} coincides with the waiting time.

In the model there are 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:

$$\max \quad \sum_s \sum_i \sum_j \sum_w \sum_z P_{is} \cdot K_{is} \cdot x_{isjwz} \tag{2}$$

$$\sum_i P_{is} \cdot x_{isjwz} \leq O_z^{max} \cdot y_{sjwz} \quad \forall s, j, w, z \tag{3}$$

$$\sum_j \sum_w \sum_z x_{isjwz} \leq 1 \quad \forall i, s \tag{4}$$

$$\sum_w \sum_j (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) \geq S_s^{min} \quad \forall s \tag{5}$$

$$\sum_w \sum_j (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) \leq S_s^{max} \quad \forall s \tag{6}$$

$$\sum_s (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) \leq 2 \quad \forall w, j \tag{7}$$

$$\sum_s y_{sjwz} \leq 1 \quad \forall w, j, z \neq d \tag{8}$$

$$\sum_j (y_{sjwm} + y_{sjwd}) \geq \gamma_{sm} \quad \forall w, s \tag{9}$$

$$\sum_j (y_{sjwa} + y_{sjwd}) \geq \gamma_{sa} \quad \forall w, s \tag{10}$$

$$\sum_j (y_{sjwm} + y_{sjwd}) \leq k \quad \forall w, k, s \in S_p^{(k)} \tag{11}$$

$$\sum_j (y_{sjwa} + y_{sjwd}) \leq k \quad \forall w, k, s \in S_p^{(k)} \tag{12}$$

$$\sum_w \sum_z \sum_{j \in NA_s} y_{sjwz} = 0 \quad \forall s \tag{13}$$

$$x_{isjwz} \in \{0, 1\} \quad \forall i, s, j, w, z \tag{14}$$

$$y_{sjwz} \in \{0, 1\} \quad \forall s, j, w, z \tag{15}$$

Constraint (4) 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 (5) and (6) 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 (7) and (8) together guarantee that there are no two surgical disciplines assigned to the same OR at the same time. More specifically, constraint (7) 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 (8) implies that, in the case of at most two half-day sessions, these are one morning and one afternoon session. Constraints (9) and (10) 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 (11) and (12) limit the number of parallel sessions assigned to the same surgical discipline. Finally, discipline-to-OR restrictions are taken into account by constraint (13).

3.3 Constrained MSS model

This model takes as input, besides the current state of each discipline waiting list, also a reference MSS. As in the previous model, this model outputs a complete plan, i.e., a MSS and a SCA. However, the MSS cannot be completely different from the reference MSS.

We define the *distance* between two given MSSs as the number of operating rooms for each day and session type assigned to different surgical disciplines across the two MSSs. Comparing the two MSSs, such a distance is determined by the number of variables y_{sjwz} having a different value in the two MSSs.

The objective function of the model is the same of the Unconstrained MSS model.

To formulate the Constrained MSS model, we add to the Unconstrained MSS model some constraints that bound the distance between the MSS computed by this model and a given reference MSS.

We introduce the following additional notation:

M_{MSS} specifies the set of OR morning sessions in the reference MSS, i.e., $(s, j, w) \in M_{MSS}$ if, in the reference MSS, on day w, OR j is assigned discipline s in a morning OR session;

A_{MSS} specifies the set of OR afternoon sessions in the reference MSS, i.e., $(s, j, w) \in A_{MSS}$ if, in the reference MSS, on day w, OR j is assigned discipline s in a afternoon OR session;

D_{MSS} specifies the set of OR full-day sessions in the reference MSS, i.e., $(s, j, w) \in D_{MSS}$ if, in the reference MSS, on day w, OR j is assigned discipline s in a full-day OR session;

N_{MSS} is the maximum number of sessions available in the OT during the week;

Δ is the maximum allowed distance between the MSS obtained by the model and 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 the same discipline 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 Constrained MSS model consists of (2)–(15) plus the constraint:

$$\sum_{(s,j,w)\in M_{MSS}} y_{sjwm} + \sum_{(s,j,w)\in A_{MSS}} y_{sjwa} + \sum_{(s,j,w)\in D_{MSS}} (y_{sjwm} + y_{sjwa} + 2y_{sjwd}) \geq N_{MSS} - \Delta \qquad (16)$$

In fact, the left-hand side of (16) 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 MSS model

In the Fixed MSS model, the MSS is given, so the decisions regarding the MSS have been already taken. Therefore, the only variables in the model concern the assignment of surgeries to OR sessions allocated to each surgical discipline. In other words, this model solves SCAP only. More specifically, let Q_s be the number of OR sessions assigned to surgical discipline s in the given MSS, and denote by O_{hs}^{max} the capacity 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:

$$\max \quad \sum_s \sum_h \sum_i P_{is} \cdot K_{is} \cdot x_{ish} \tag{17}$$

$$\sum_h x_{ish} \leq 1 \quad \forall i, s \tag{18}$$

$$\sum_i P_{is} \cdot x_{ish} \leq O_{hs}^{max} \quad \forall s, h \tag{19}$$

$$x_{ish} \in \{0, 1\} \quad \forall i, s, h \tag{20}$$

Observe that the Fixed MSS model can be decomposed into several bin filling problems, one for each surgical discipline, in which surgeries correspond to items and sessions to bins.

3.5 Heuristics

The mathematical models introduced in the previous sections may in general require large computation times, even to find suboptimal solutions. Therefore, in order to quickly reach good solutions to MSSP and SCAP, we propose an efficient heuristic approach. The idea is to adopt a decomposition scheme addressing the two problems sequentially, i.e., a first heuristic algorithm produces the MSS while a second heuristic takes the MSS as input and determines the SCA.

3.5.1 Determining the MSS

The algorithm that produces the MSS works as follows. First, (i) based on the waiting list of each surgical discipline, we quickly generate a few sets of surgeries, such that each set can fit an OR session. This way, for each discipline a set of *candidate* OR sessions is produced. Next, (ii) a complete surgical case assignment is temporarily produced selecting some of these candidate OR sessions. Thereafter, (iii) all surgical cases are discarded, and only the MSS is retained.

In step (i), for each surgical discipline s we generate a number of candidate OR sessions, of various types. To this aim, we consider the problem of filling a number of bins (the OR sessions) of given capacity (the OR session capacity) with items (the surgical cases), each having a certain size (the processing time of the surgical case). Now, if S_s^{max} is even, we consider $S_s^{max}/2$ bins of capacity O_m^{max} corresponding to morning sessions and $S_s^{max}/2$ bins of capacity O_a^{max} corresponding to afternoon sessions. If S_s^{max} is odd, we consider $\lceil S_s^{max}/2 \rceil$ bins of capacity O_m^{max} corresponding to morning sessions and $\lceil S_s^{max}/2 \rceil - 1$ bins of capacity O_a^{max} corresponding to afternoon sessions. Then, we order all the surgical cases of discipline s by nonincreasing score, and sequentially fill the bins according to the first-fit-decreasing rule, i.e., assigning the current item to the first bin that fits. (Bins corresponding to morning and afternoon sessions are considered alternately.) In this way, we generate S_s^{max} candidate OR sessions. Then, we repeat the whole process, but with $\lfloor S_s^{max}/2 \rfloor$ bins of capacity O_d^{max}, hence generating as many full-day sessions. Note that while candidate sessions of the same type are all disjoint, a full-day and a morning (or afternoon) candidate sessions may have nonempty intersection.

In step (ii), we select a subset of the candidate OR sessions generated, to produce a feasible plan.

To this aim, once the candidate OR sessions for each surgical discipline have been generated, we compute the value v_{szf} of each candidate OR session f of type z for the surgical discipline s by adding the values $P_{is}K_{is}$ for all surgical cases in that session. If the f-th full-day session and the g-th morning (or afternoon session) have some surgical case in common, they are *incompatible*. Let L be the list of all pairs $((d,f);(m,g))$ or $((d,f);(a,g))$ such that the corresponding candidate OR sessions are incompatible.

At this point, we formulate and solve the following mathematical programming problem. Here the decision variables are defined as $y_{sjwzf} = 1$ if the f-th candidate session of type z for the surgical discipline s is assigned to OR j during day w.

$$\max \quad \sum_s \sum_z \sum_f \big(v_{szf} \cdot \sum_j \sum_w y_{sjwzf}\big) \tag{21}$$

$$\sum_j \sum_w y_{sjwzf} \leq 1 \quad \forall s, z, f \tag{22}$$

$$\sum_j \sum_w \sum_f \big(y_{sjwmf} + y_{sjwaf} + 2y_{sjwdf}\big) \geq S_s^{min} \quad \forall s \tag{23}$$

$$\sum_j \sum_w \sum_f \big(y_{sjwmf} + y_{sjwaf} + 2y_{sjwdf}\big) \leq S_s^{max} \quad \forall s \tag{24}$$

$$\sum_s \sum_f \big(y_{sjwmf} + y_{sjwaf} + 2y_{sjwdf}\big) \leq 2 \quad \forall j, w \tag{25}$$

$$\sum_s \sum_f y_{sjwzf} \leq 1 \quad \forall j, w, z \neq d \tag{26}$$

$$\sum_j \sum_f (y_{sjwmf} + y_{sjwdf}) \geq \gamma_{sm} \quad \forall w, s \tag{27}$$

$$\sum_j \sum_f (y_{sjwaf} + y_{sjwdf}) \geq \gamma_{sa} \quad \forall w, s \tag{28}$$

$$\sum_j \sum_f (y_{sjwmf} + y_{sjwdf}) \leq k \quad \forall w, k, s \in S_p^{(k)} \tag{29}$$

$$\sum_j \sum_f (y_{sjwaf} + y_{sjwdf}) \leq k \quad \forall w, k, s \in S_p^{(k)} \tag{30}$$

$$\sum_{w}\sum_{z}\sum_{j\in NA_s}\sum_{f} y_{sjwzf} = 0 \quad \forall s \tag{31}$$

$$\sum_{j}\sum_{w}(y_{sjwdf} + y_{sjwmg}) \leq 1 \quad \forall s, ((d,f);(m,g)) \in L \tag{32}$$

$$\sum_{j}\sum_{w}(y_{sjwdf} + y_{sjwag}) \leq 1 \quad \forall s, ((d,f);(a,g)) \in L \tag{33}$$

$$y_{sjwzf} \in \{0,1\} \quad \forall s,j,w,z,f \tag{34}$$

The objective function (21) is given by the sum of the values of the candidate OR sessions selected. Constraints (22)–(31) have the same meaning of the corresponding constraints in (4)–(13). Constraints (32) and (33) avoid that two incompatible OR sessions are selected.

The output of the model is an assignment of sessions to ORs. At this point, in step (*iii*), we only retain the MSS structure, discarding all surgical cases. The MSS is the input to the next phase, consisting in finding a heuristic solution to SCAP.

Note that we supposed not to have any constraint on the structure of the MSS, i.e., the heuristic proposed in this section has been described with reference to the Unconstrained MSS case (see Section 3.2). However, it can be easily adapted to address also the Constrained MSS case (Section 3.3), using the same step (*i*) and solving step (*ii*) by adding the following constraint (35) to the model, which is a suitable modification of constraint (16).

$$\sum_{(s,j,w)\in M_{MSS}}\sum_{f} y_{sjwmf} + \sum_{(s,j,w)\in A_{MSS}}\sum_{f} y_{sjwaf} + \sum_{(s,j,w)\in D_{MSS}}\sum_{f} (y_{sjwmf} + y_{sjwaf} + 2y_{sjwdf}) \geq N_{MSS} - \Delta \tag{35}$$

where M_{MSS}, A_{MSS}, and D_{MSS} are defined as in Section 3.3.

3.5.2 Heuristic for SCAP

Given an MSS (either provided by OT management, as for the Fixed MSS case, or computed through the heuristic discussed in Section 3.5.1, as for the Unconstrained and Constrained MSS cases), we now solve SCAP through the following heuristic. Again, we consider each OR session in the MSS as a bin of given capacity O_z^{max}, related to the OR session type z. Assigning a surgical case i to an OR session of discipline s corresponds to filling the bin with an item, of size P_{is}. For each discipline s, we order the case surgeries in the waiting list I_s by nonincreasing score K_{is}. Next, we consider all the OR sessions in the MSS assigned to discipline s and fill them picking the surgical cases from the sorted waiting list, following a first-fit-decreasing rule as we did in Section 3.5.1. Figure 1 illustrates the main steps of the heuristic solving SCAP; as further notation, we introduce Ψ_s to denote the set of OR sessions ($|\Psi_s| = Q_s$) assigned to surgical discipline s in the given MSS, and $\sigma_{(i)}$ denotes the surgical case ranked i in the ordered waiting list $I_{s,sort}$.

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 Empoli (Tuscany, Italy). More specifically, in Section 4.1 we present the details on the case study, and in Section 4.2 we illustrate the numerical results obtained.

SCAP heuristic

Input:
MSS;
waiting list I_s of discipline s, $s = 1, \ldots, |S|$;

begin
for each $s = 1, \ldots, |S|$
Select all OR sessions assigned to s in the MSS, obtaining an array Ψ_s, $|\Psi_s| = Q_s$
Sort I_s by nonincreasing score K_{is}, giving the sequence
$I_{s,sort} = \{\sigma_{(1)}, \sigma_{(2)}, \ldots, \sigma_{(|N_s|)}\}$ such that $K_{(1)s} \geq K_{(2)s} \geq \ldots \geq K_{(|N_s|)s}$
for each surgical case $\sigma_{(i)} \in I_{s,sort}$
//Find the first OR session in Ψ_s *in which* $\sigma_{(i)}$ *fits*
for each session $h = 1, \ldots, Q_s$
if $\sigma_{(i)}$ fits h
Assign surgical case $\sigma_{(i)}$ to session h
end

Figure 1: Main steps of the heuristic for SCAP

4.1 Case study

Here we first describe the characteristics of the OT in Section 4.1.1. Section 4.1.2 describes the solution approaches and the performance indices designed to evaluate our alternative planning policies on the specific case study. Then, detailed information on the setting used for the computational experiments is given in Section 4.1.3.

4.1.1 Characteristics of the OT and models implications

Based on the real case study, we consider an operating theater composed of $|J| = 6$ operating rooms: they are all identically equipped, even though two of them (say, $j = 5, 6$) are bigger than the others.

Surgeries belong to the following disciplines: general surgery (s = GS), otolaryngology, referred to as Ear-Nose-Throat surgery (s = ENT), gynecology (s = GYN), orthopedic surgery (s = ORTH), and urology (s = URO); moreover, for modeling purposes and upon OT manager's suggestion, we consider day surgery (s = DS) as a discipline by itself, given that it consists of short surgeries only, so they can be managed more effectively if accounted for separately from the ordinary surgeries. Thus, the set of surgical disciplines is $S = \{\text{GS}, \text{ENT}, \text{GYN}, \text{ORTH}, \text{URO}, \text{DS}\}$.

Some organizational restrictions hold for the OR assignment to the surgical disciplines; in particular:

- Gynecology surgeries should be performed in the same OR for the whole week; e.g., without loss of generality we assign the OR $j = 1$ to s = GYN, so that $NA_{\text{GYN}} = \{2, 3, 4, 5, 6\}$. Nevertheless, this OR is not reserved to gynecology only.

- Orthopedic surgeries have to be performed in a big OR; i.e., either in $j = 5$ or in $j = 6$. Thus, $NA_{\text{ORTH}} = \{1, 2, 3, 4\}$. Nevertheless, these two ORs are not exclusively used by orthopedics.

- General surgery and orthopedic surgery allow $k = 2$ parallel OR sessions, whereas all the other surgical disciplines do not admit parallel sessions. Therefore, following the notation introduced in Section 3.1, we set $S_p^{(1)} = \{\text{ENT}, \text{GYN}, \text{URO}, \text{DS}\}$, $S_p^{(2)} = \{\text{GS}, \text{ORTH}\}$ and $S_p^{(k)} = \emptyset$ for $k = 3, \ldots, 6$.

Focusing on elective surgeries only, the weekly surgery plan spans five days, from Monday to Friday. No elective surgeries are scheduled during the weekend. For hospital management reasons, the plan is prepared one week ahead, on Monday. All session types are divided into time slots of 15 minutes each. A morning session lasts 26 time slots, an afternoon session 20 time slots, and a full-day session 46 time slots. However, due to hospital policies, we leave two free time slots in each half-day session ($z = m, a$) and four free time slots in each full-day session ($z = d$), as a planned slack time to account 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, 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). This is modeled through constraint (9), letting $\gamma_{sm} = 1$ for $s = \text{DS}$, and replacing the inequality with an equality. To reserve one OR to emergencies every afternoon, the following constraints (36) are added to both the Unconstrained and the Constrained MSS problem formulations.

$$\sum_s \sum_j (y_{sjwa} + y_{sjwd}) \leq |J| - 1 \quad \forall w \,. \tag{36}$$

Then, the maximum number of OR sessions available in one week is $N_{MSS} = 2$ (OR sessions/day) $\cdot\, 5$ (days/week) $\cdot\, 6$ (ORs) $- 5$ (empty OR sessions/week) $= 55$.

Finally, the following constraints (37) are added to the Unconstrained and Constrained MSS model formulations:

$$y_{sjwm} + y_{sjwa} \leq 1 \quad \forall s, j, w \tag{37}$$

These constraints state that a full-day session has to be preferred with respect to a morning + an afternoon session assigned to the same surgical discipline in the same room, for the same day. Note that these constraints are not strictly necessary from the modeling viewpoint (the overall duration being the same, case surgeries of a given discipline assigned to two half-day sessions can always be scheduled in a full-day session, whereas the reverse is not true in general), but have been introduced for computational purposes.

Similar constraints to (36) and (37) are added to the heuristic formulation of both the Unconstrained MSS and the Constrained MSS models.

Although our models allow to set an explicit constraint on the maximum number of weekly sessions S_s^{max} assigned to a single surgical discipline s (constraint (6)), in our case study the hospital management did not use such option. However, S_s^{max} is bounded by the effects of the constraints (11)–(12) on the maximum number k of parallel sessions for discipline s, being $S_s^{max} = 2 \cdot k \cdot 5$ where k is either 1 or 2.

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. Class A surgeries are the most urgent, and have a maximum allowed waiting time $W_A = 30$ days. Class B surgeries have $W_B = 60$ days, while class C surgeries have $W_C = 90$ days. Depending on the priority class c_{is}, the OT management defines a weight coefficient $\pi_{is} = 5$ for class A surgeries ($c_{is} = A$), $\pi_{is} = 2$ for class B surgeries ($c_{is} = B$) and $\pi_{is} = 1$ for class C surgeries ($c_{is} = C$). These weights, included in the objective function using Score 1, induce the models to select surgical cases with higher priority.

We conclude this section with a technical issue. Due to the presence of identical ORs, our mathematical programs for Unconstrained and Constrained MSS have many equivalent symmetric solutions, we introduce a set of symmetry-breaking constraints (38)–(43). These do not rule out the optimal solution, and have the sole purpose of efficiently restricting the set of feasible solutions, thus reducing the computational burden. We define an arbitrary ordering of the four surgical disciplines for which $NA_s = \emptyset$, namely

$$\text{DS} \prec \text{URO} \prec \text{ENT} \prec \text{GS}$$

and we use this ordering in the assignment of available ORs for increasing values of room index. For instance, if DS has been assigned to the operating room $j+1$, then none of rooms $1, 2, \ldots, j$ can be assigned to either URO, ENT or GS in the same half-day; see (38)–(39).

$$\sum_{z \neq a} \left(y_{\text{DS},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad \forall s \in \{\text{URO}, \text{ENT}, \text{GS}\}, w, j \in \{1, \ldots, |J|-1\} \tag{38}$$

$$\sum_{z \neq m} \left(y_{\text{DS},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad \forall s \in \{\text{URO}, \text{ENT}, \text{GS}\}, w, j \in \{1, \ldots, |J|-1\} \tag{39}$$

$$\sum_{z \neq a} \left(y_{\text{URO},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad \forall s \in \{\text{ENT}, \text{GS}\}, w, j \in \{1, \ldots, |J|-1\} \tag{40}$$

$$\sum_{z \neq m} \left(y_{\text{URO},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad \forall s \in \{\text{ENT}, \text{GS}\}, w, j \in \{1, \ldots, |J|-1\} \tag{41}$$

$$\sum_{z \neq a} \left(y_{\text{ENT},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad s = gs, \forall w, j \in \{1, \ldots, |J|-1\} \tag{42}$$

$$\sum_{z \neq m} \left(y_{\text{ENT},j+1,wz} + \sum_{k=1}^{j} y_{skwz} \right) \leq 1 \qquad s = \text{GS}, \forall w, j \in \{1, \ldots, |J|-1\} \tag{43}$$

4.1.2 Planning policies and performance indices

We perform our simulations on alternative planning policies, as discussed in Section 3. We code the policies as 'XYZ', where 'X' denotes the MSS model (U = unconstrained, C = constrained, F = fixed), 'Y' specifies how MSSP is solved (E = exactly, H = heuristically, '_' (blank) when an MSS is given, so MSSP is not solved), 'Z' specifies how SCAP is solved (E = exactly, H = heuristically). We use a '·' for a field whenever the statement applies to all values of that field.

UEE Unconstrained MSS model, solved through the mathematical formulation discussed in Section 3.2;

CEE Constrained MSS model, solved through the mathematical formulation discussed in Section 3.3;

F_E Fixed MSS model, solved through the mathematical formulation discussed in Section 3.4;

UHH Unconstrained MSS model, heuristically solved as in Section 3.5;

CHH Constrained MSS model, heuristically solved adding constraint (35) to the formulation provided in Section 3.5;

F_H Fixed MSS model, solved through the heuristic for SCAP (see Section 3.5.2 and Figure 1);

UHE Unconstrained MSS hybrid model, which first solves MSSP through the heuristic algorithm discussed in Section 3.5.1, and then uses the MSS just found to solve SCAP exactly, according to the formulation in Section 3.4;

CHE Constrained MSS hybrid model, which solves SCAP exactly as in Section 3.4, using the MSS derived from the heuristic described in Section 3.5, including constraint (35).

When solving the constrained MSS model (either optimally or heuristically), we define a *block* (weeks) as a time interval during which the MSS remains fixed. Changes in an MSS can therefore occur only between the last week of a block and the first week of the next block. Following our notation, these characteristics are specified in a compact way by appending two numbers to the string 'C $\cdot\cdot$', as follows: 'C $\cdot\cdot|b$-Δ' denotes a constrained model having a block time of b weeks and maximum distance Δ between the MSS of a block and the MSS of the previous block, taken as reference MSS.

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*) % empty time slots: residual time not assigned to any surgery, as percentage of the overall number of time slots available in the week;

(*iii*) % empty time slots *: residual time not assigned to any surgery, due to empty waiting lists, as percentage of the overall number of time slots available in the week;

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

(*v*) ♯ weighted late cases: number of late surgical cases weighted by their respective priority class coefficient;

(*vi*) 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;

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

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

(*ix*) 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;

Table 1: Cardinality of the surgery waiting lists in the base scenario at the beginning of the simulation.

Surgical Discipline	s	N_s	$min_i P_{is}$	$max_i P_{is}$
General Surgery	GS	230	5	30
Gynecology	GYN	244	3	18
Orthopedic Surgery	ORTH	429	2	12
Urology	URO	112	3	14
Otolaryngology	ENT	101	2	10
Day Surgery	DS	257	2	5

(x) computing time: CPU time (seconds) to solve the problem.

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

Furthermore, for each policy and for each objective function, 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 following indicators:

- $\mathcal{N}$ denotes the average current length of the waiting lists, computed as

$$\mathcal{N} = \frac{1}{|S|} \sum_s N_s \, ; \tag{44}$$

- $\mathcal{T}$ denotes the average waiting time of the case surgeries currently in the waiting list, computed as

$$\mathcal{T} = \frac{1}{|S|} \sum_s \left(\frac{1}{N_s} \sum_{i \in I_s} T_{is} \right) \, ; \tag{45}$$

- $\mathcal{R}$ denotes the average slack time of the case surgeries currently in the waiting list, computed as

$$\mathcal{R} = \frac{1}{|S|} \sum_s \left(\frac{1}{N_s} \sum_{i \in I_s} R_{is} \right) \, . \tag{46}$$

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.

We simulate the system and evaluate its performance under alternative planning policies for 52 weeks. The input of the first week of our simulation consists of the current waiting lists provided by the hospital — which we will refer to as *base lists*. Recalling that, for each surgical discipline s, $N_s = |I_s|$, we let $N = \sum_s N_s$. Table 1 summarizes the cardinality of the base list for each surgical discipline, at the beginning of the simulation, including minimum and maximum duration (time slots) of surgeries.

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. We assume that there is a random number of arrivals n each week, sampled from a distribution estimated by OT managers, namely, a uniform distribution centered around the average weekly arrival rate:

$$n \sim Unif(140, 240) \tag{47}$$

Given the number of weekly arrivals n, new surgeries are obtained through nonparametric bootstrapping [8], which consists in sampling n_s surgeries — with replacement — from the initial waiting list I_s, where

$$n_s = \frac{N_s}{N} n \tag{48}$$

We refer to this experimental setting as the *base scenario*.

A second experimental setting is aimed at simulating the behavior of the system starting from a congested condition, which may occasionally derive from an exceptionally high rate of non-elective surgery, and/or unpredicted demand variability. 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 consider a *stressed scenario*, in which a number of late surgeries belonging to these disciplines are added to I_{DS} and I_{GS}. In particular, we add 100 surgeries to I_{GS} and 100 to I_{DS}, representing about 40% of N_s for $s = \text{GS}, \text{DS}$, and almost 15% of N. All these additional surgeries are assumed to be $2W_C = 180$ days late, i.e., their slack time (Section 3.1) is $R_{is} = -180$, for $s = \text{GS}, \text{DS}; i = N_s + 1, \ldots, N_s + 100$.

To enable a fair comparison among the planning policies taken into account, the same arrivals of new case surgeries throughout the 52 weeks have been used in all simulations, both in the base scenario and in the stressed scenario, no matter which planning policy is adopted and which objective function is optimized.

In our tests, we adopt two settings for the block length and maximum distance in the Constrained MSS model — as suggested by the OT management, based on staff willingness to accept them, namely, (*i*) $b = 1, \Delta = 1$ (one change per week) and (*ii*) $b = 4, \Delta = 2$ (two changes every four weeks).

For the Fixed MSS model, we use the MSS currently adopted in the hospital, which is shown in Table 2.

For each planning policy and the two alternative scenarios, we solve two optimization problems, differing in the objective function. In what follows, we denote by f_1 the objective function using Score 1, i.e. $K_{is} = (T_{is} \cdot \pi_{is})$, and by f_2 the objective function using Score 2, i.e. with $K_{is} = (W_C - R_{is})$ (Section 3.2).

The maximum computation time has been set to 30 minutes for each optimization run. Tests have been performed on a 2.53 GHz Intel Xeon processor with 6 GB of RAM, using OPL Studio 6.1 and the CPLEX 11.2 MILP solver for the mathematical programming models and standard C++ for the heuristic models.

4.2 Numerical results

We now discuss the performances of the proposed planning policies, evaluated through the indices presented in Section 4.1.2, averaged over 52 weeks. These results are organized in four tables, in which each row corresponds to a policy and the columns refer to the performance indices. Tables 3 and 4 refer to the base scenario, optimizing f_1 and f_2 respectively, while

Table 2: MSS adopted in the Fixed Model.

	$w = 1$	$w = 2$	$w = 3$	$w = 4$	$w = 5$
$j = 1$	$z = m$ $z = a$ GYN `empty`	$z = d$ GYN	$z = d$ GYN	$z = m$ $z = a$ GYN URO	$z = d$ GYN
$j = 2$	$z = d$ DS	$z = m$ $z = a$ ENT `empty`	$z = d$ DS	$z = d$ DS	$z = d$ DS
$j = 3$	$z = d$ GS	$z = d$ DS	$z = d$ gs	$z = d$ gs	$z = d$ gs
$j = 4$	$z = d$ ENT	$z = d$ GS	$z = d$ URO	$z = d$ ENT	$z = d$ URO
$j = 5$	$z = d$ ORTH	$z = d$ ORTH	$z = d$ ORTH	$z = m$ $z = a$ ORTH `empty`	$z = d$ ORTH
$j = 6$	$z = d$ ORTH	$z = d$ ORTH	$z = m$ $z = a$ ORTH `empty`	$z = d$ ORTH	$z = m$ $z = a$ ORTH `empty`

Table 3: Performances of planning policies (averaged over 52 weeks) in the base scenario, for objective function f_1

	♯ cases	% empty t.s.	% empty t.s.*	♯ late cases	weighted ♯late cases	mean lateness (days)	max lateness (days)	waiting time (days)	mean tardiness (days)	computing time (s)
UEE	194	0.05	0	23	44	-16	13	57	7	1710
CEE|1-1	192	0.17	0	32	58	-16	32	57	8	504
CEE|4-2	193	0.09	0	27	54	-16	23	58	7	156
F_E	183	0.42	0.35	67	130	-13	65	58	11	30
UHH	192	0.85	0	26	59	-15	18	59	7	1
CHH|1-1	192	0.89	0	28	69	-15	28	58	7	1
CHH|4-2	192	0.85	0	29	73	-15	32	58	7	< 1
F_H	183	1.01	0.35	69	140	-13	61	61	11	< 1
UHE	194	0.06	0	23	45	-16	14	58	7	30
CHE|1-1	193	0.07	0	27	54	-16	21	57	7	34
CHE|4-2	193	0.08	0	27	55	-16	23	58	7	29

Tables 6 and 7 refer to the stressed scenario. Then, we report the comparison of the status of the waiting lists at the end of the simulated period. These comparisons are shown in Tables 5-10.

4.2.1 Base scenario

Tables 3 and 4 report the results for the base scenario. A few comments are in order.

- The overall performances of the proposed planning policies when optimizing f_1 and f_2 are mostly comparable. However, f_1 is slightly better in terms of weighted number of late cases and f_2 in terms of maximum lateness. For both objective functions, all the policies schedule a similar number of surgical cases, except for the fixed MSS models (F_E and F_H), which — on average — schedule a slightly smaller number of surgical cases.

- As for the percentage of empty time slots, all the policies provide an efficient use of the OT. All Unconstrained and Constrained policies using the exact model for SCAP fill OR sessions almost perfectly, while the worst is F_H (spoiling about 1% of the time).

- F_E and F_H provide the worst performance in terms of empty time slots due to empty waiting lists (third column). In fact, keeping the MSS fixed, when one or more waiting

Table 4: Performances of planning policies (averaged over 52 weeks) in the base scenario, for objective function f_2

	♯ cases	% empty t.s.	% empty t.s.*	♯ late cases	weighted ♯late cases	mean lateness (days)	max lateness (days)	waiting time (days)	mean tardiness (days)	computing time (s)
UEE	194	0.05	0	24	48	-16	5	57	7	1692
CEE|1-1	191	0.27	0	38	74	-16	23	67	13	558
CEE|4-2	193	0.08	0	35	76	-16	18	58	7	150
F_E	184	0.45	0.36	65	138	-14	41	61	13	42
UHH	192	0.76	0	27	67	-15	20	58	7	1
CHH|1-1	192	0.79	0	29	74	-16	27	58	7	1
CHH|4-2	191	0.77	0.02	32	80	-16	34	58	7	< 1
F_H	184	0.97	0.35	67	140	-14	54	60	10	< 1
UHE	193	0.05	0	25	51	-15	7	58	7	34
CHE|1-1	193	0.05	0	29	61	-16	13	58	7	40
CHE|4-2	193	0.08	0.01	33	72	-16	17	57	7	42

lists have been emptied, 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 (first column).

- On the whole, the performance obtained with the Constrained MSS models is significantly better than fixed-MSS models (F_E and F_H) and only slightly worse than Unconstrained MSS models. This is true for both Constrained models ($C \cdot\cdot |4\text{-}2$ and $C \cdot\cdot |1\text{-}1$), with no clear dominance between them. This suggests that the introduction of an even small amount of flexibility in the definition of the weekly MSS appears as extremely beneficial, cutting figures such as the average (weighted or unweighted) number of late cases and maximum lateness by about one half. Actually, to support the choice of the planning policy to be implemented in the OT, it is relevant to compute the distance between the MSSs of two consecutive weeks as determined by the unconstrained models. We recorded that, when using the unconstrained models, the average distance between two consecutive MSSs is 12.5 OR sessions, varying between 5 and 37 throughout the year. Being $N_{MSS} = 55$, this means that on average the unconstrained MSS model changes 20% of the whole MSS every week, with a worst case of 67%. On the other hand, the constrained MSS model provides a much higher stability, by changing less than 2% of the whole MSS every week when $\Delta = 1$ and $b = 1$, and less than 1% when $\Delta = 2$ and $b = 4$.

- Mean lateness has similar values for all planning policies. Anyway, the various policies differ much more significantly when considering the maximum lateness and mean tardiness across surgical cases.

- As expected, the policies solving both MSSP and SCAP exactly (i.e., ·EE policies) require the highest computing time, while the policies based on heuristics (i.e., ·HH policies) are the fastest. For a given MSS model, the solutions provided by the ·EE policies guarantee the best quality in terms of the performance indicators shown in Tables 3 and 4. Finally, ·HE policies spend a reasonable computing time to solve the two problems MSSP and SCAP, keeping the quality of the corresponding solutions satisfactory. A significant worsening in the performance indicators is observed for ·HH policies.

Table 5 compares the initial waiting lists (first column, $L_0 = \bigcup_s I_s$ at the beginning of the simulated period) and the final waiting lists (at the end of the simulated period) produced

Table 5: Comparison between initial and final waiting list for each planning policy in the base scenario, for both objective functions f_1 and f_2

		L_0	UEE		CEE|1-1		CEE|4-2		F_E		UHH		CHH|1-1		CHH|4-2		F_H		UHE		CHE|1-1		CHE|4-2	
			f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
A	$\mathcal{N}$	26.2	5.5	3.0	5.2	3.2	5.7	7.7	11.0	17.2	9.7	7.8	9.5	8.5	9.2	9.0	19.8	21.3	6.5	3.0	6.7	3.0	6.7	3.0
	$\mathcal{T}$	56.4	2.6	0.0	2.3	1.2	3.2	3.5	6.7	9.3	6.5	4.5	6.4	5.0	6.4	5.3	13.7	15.7	3.1	0.0	3.8	0.0	3.8	0.0
	$\mathcal{R}$	-26.4	27.4	30.0	27.7	28.8	26.8	26.5	23.3	20.7	23.5	25.5	23.6	25.0	23.6	24.7	16.3	14.3	26.9	30.0	26.2	30.0	26.2	30.0
B	$\mathcal{N}$	68.8	33.2	29.3	35.0	38.2	37.2	54.8	84.5	85.0	38.7	31.0	40.2	34.3	40.2	36.8	78.5	80.3	37.2	32.2	37.5	36.7	38.0	35.7
	$\mathcal{T}$	81.3	9.7	5.7	10.1	11.2	10.0	12.6	17.7	18.6	11.4	8.9	12.1	9.5	11.5	10.4	16.9	18.0	10.0	8.5	10.2	9.3	9.6	7.6
	$\mathcal{R}$	-21.3	50.3	54.3	49.9	48.8	50.0	47.4	42.3	41.4	48.6	51.1	47.9	50.5	48.5	49.6	43.1	42.0	50.0	51.5	49.8	50.7	50.4	52.4
C	$\mathcal{N}$	133.8	122.2	129.7	137.0	140.0	123.7	154.2	154.7	143.2	127.0	134.3	127.3	132.5	127.3	133.3	153.3	145.8	118.7	130.2	119.0	126.8	119.3	126.3
	$\mathcal{T}$	90.8	19.1	22.6	19.2	20.4	21.4	28.4	32.8	25.7	23.6	24.6	24.6	24.7	23.2	26.3	24.4	23.2	21.6	24.1	21.7	24.2	21.2	20.2
	$\mathcal{R}$	-0.8	70.9	67.4	70.8	69.6	68.6	61.6	57.2	64.3	66.4	65.4	65.4	65.3	66.8	63.7	65.6	66.8	68.4	65.9	68.3	65.8	68.8	69.8
Tot	$\mathcal{N}$	228.8	160.8	162.0	177.2	181.3	166.5	216.7	250.2	245.3	175.3	173.2	177.0	175.3	176.7	179.2	251.7	247.5	162.3	165.3	163.2	166.5	164.0	165.0
	$\mathcal{T}$	89.4	15.3	17.2	15.8	16.5	16.4	23.9	22.2	20.3	17.9	18.6	18.8	19.0	18.1	20.5	21.4	20.4	16.1	18.6	16.4	19.0	15.8	16.3
	$\mathcal{R}$	-16.6	62.7	63.3	61.3	60.9	61.4	56.1	53.9	54.8	58.8	59.9	58.3	59.2	58.6	58.2	53.8	54.3	61.8	61.6	61.5	61.1	62.0	61.5

Table 6: Performances of planning policies (averaged over 52 weeks) in the stressed scenario, for objective function f_1

	♯ cases	% empty t.s.	% empty t.s.*	♯ late cases	♯ weighted late cases	mean lateness (days)	max lateness (days)	waiting time (days)	mean tardiness (days)	computing time (s)
UEE	194	0.03	0	29	54	-3.79	22	70	12	1758
CEE|1-1	192	0.14	0	42	80	-3.25	42	70	12	528
CEE|4-2	193	0.07	0	45	82	-3.58	40	70	12	162
F_E	185	0.39	0.3	80	158	-3.5	86	67	19	30
UHH	192	0.76	0	33	75	-2.83	29	71	12	2
CHH|1-1	192	0.97	0	39	86	-3.17	38	70	12	1
CHH|4-2	192	0.95	0	40	92	-3.67	43	70	12	< 1
F_H	185	0.98	0.3	85	171	-3.71	81	70	18	< 1
UHE	193	0.05	0	30	55	-3.92	23	70	12	36
CHE|1-1	193	0.05	0	55	90	-4.42	35	69	12	31
CHE|4-2	194	0.09	0	60	98	-4.71	43	69	13	27

by each policy (following columns) in the base scenario, for both objective functions f_1 and f_2. The comparison is done averaging over the disciplines, and is based on the indicators introduced in Section 4.1.2, namely the average length of the waiting lists ($\mathcal{N}$), the average waiting time of the case surgeries currently in the waiting lists ($\mathcal{T}$), and the average slack time of the case surgeries currently in the waiting lists ($\mathcal{R}$). These indicators have been computed separately for each priority class (rows associated with A, B, and C, respectively) and for the whole waiting list (rows associated with Tot).

Almost all policies provide a waiting list at the end of the simulated period which is shorter than the initial one, except for the policies based on a fixed MSS model. Nevertheless, even for these policies, both the average waiting time and the average slack time improved w.r.t. the initial waiting list.

All the proposed policies show a fair management of the three priority classes, for both the objective functions. Notice that this is due to the way we defined f_2, whereas alternative management's choices of the weight coefficients π_{is} in f_1 would imply surgical cases belonging to each priority class to be managed differently.

4.2.2 Stressed scenario

Tables 6 and 7 show the performances of the proposed planning policies in the stressed scenario, when optimizing f_1 and f_2 respectively. The results are similar to those observed in Tables 3-4, although most indicators take higher values than in the base scenario, especially in terms of ORs utilization and delays. Again, F_H and F_E appear as the worst performing policies, while the policies based on the unconstrained MSS model perform reasonably well also in the stressed scenario.

Table 7: Performances of planning policies (averaged over 52 weeks) in the stressed scenario, for objective function f_2

	♯ cases	empty t.s.	empty t.s.*	♯ late cases	♯ weighted late cases	mean lateness (days)	max lateness (days)	waiting time (days)	mean tardiness (days)	computing time (s)
UEE	193	0.02	0	30	59	-4	17	69	11	1776
CEE|1-1	191	0.21	0	52	102	-3.88	42	83	22	510
CEE|4-2	193	0.03	0	48	106	-3.71	35	70	12	150
F_E	186	0.38	0.31	79	164	-4.29	57	75	23	42
UHH	192	0.65	0	35	83	-3	32	71	12	1
CHH|1-1	192	0.77	0	40	94	-3.58	39	70	12	1
CHH|4-2	192	0.77	0	40	92	-3.67	39	70	12	< 1
F_H	186	0.88	0.3	82	163	-4.5	70	70	17	< 1
UHE	193	0.02	0	35	71	-3.33	21	70	12	37
CHE|1-1	193	0.08	0	46	97	-4.17	29	69	12	36
CHE|4-2	193	0.03	0	41	89	-3.92	29	69	12	33

Table 8: Comparison between initial and final waiting list for each planning policy in the stressed scenario, for both objective functions f_1 and f_2

		L_0	UEE		CEE|1-1		CEE|4-2		F_E		UHH		CHH|1-1		CHH|4-2		F_H		UHE		CHE|1-1		CHE|4-2	
			f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
A	$\mathcal{N}$	27.0	6.7	3.0	7.3	3.5	7.3	3.5	11.8	19.2	10.7	8.5	10.2	8.7	12.0	9.0	20.8	23.0	7.0	3.0	6.8	3.2	8.0	3.3
	$\mathcal{T}$	60.1	3.8	0.0	4.9	2.5	4.4	0.5	8.7	14.8	7.1	5.7	6.8	5.8	7.7	6.0	15.1	17.6	4.4	0.0	3.9	0.2	4.8	0.9
	$\mathcal{R}$	-30.1	26.2	30.0	25.1	27.5	25.6	29.5	21.3	15.2	22.9	24.3	23.2	24.2	22.3	24.0	14.9	12.4	25.6	30.0	26.1	29.8	25.2	29.1
B	$\mathcal{N}$	75.3	42.0	38.7	44.7	45.8	46.3	49.3	86.0	88.2	46.5	45.0	47.8	44.3	50.3	43.3	80.3	84.5	45.3	44.3	46.0	48.0	45.5	44.2
	$\mathcal{T}$	94.4	12.0	11.0	12.7	14.2	12.6	12.0	18.7	20.8	13.8	12.5	14.3	12.0	15.6	11.8	18.2	20.8	12.4	12.2	12.4	12.3	11.6	12.7
	$\mathcal{R}$	-34.4	48.0	49.0	47.3	45.8	47.4	48.0	41.3	39.2	46.2	47.5	45.7	48.0	44.4	48.2	41.8	39.2	47.6	47.8	47.6	47.7	48.4	47.3
C	$\mathcal{N}$	159.8	147.5	156.0	155.5	166.5	146.2	148.2	173.2	156.3	153.2	154.7	153.7	156.0	148.5	157.5	170.2	157.7	146.7	153.7	144.8	149.0	141.0	154.0
	$\mathcal{T}$	110.8	24.1	27.6	26.7	27.8	26.3	28.1	36.2	27.9	28.1	28.9	27.7	27.4	27.1	28.4	27.2	25.2	26.8	28.9	25.6	27.1	24.1	28.4
	$\mathcal{R}$	-20.8	65.9	62.4	63.3	62.2	63.7	61.9	53.8	62.1	61.9	61.1	62.3	62.6	62.9	61.6	62.8	64.8	63.2	61.1	64.4	62.9	65.9	61.6
Tot	$\mathcal{N}$	262.2	196.2	197.7	207.5	215.8	199.8	201.0	271.0	263.7	210.3	208.2	211.7	209.0	210.8	209.8	271.3	265.2	199.0	201.0	197.7	200.2	194.5	201.5
	$\mathcal{T}$	102.5	19.6	21.6	21.1	22.8	20.2	22.4	25.0	22.3	22.4	22.8	22.1	21.8	21.5	22.2	23.9	22.4	20.6	23.1	19.9	21.7	18.3	23.2
	$\mathcal{R}$	-29.5	58.3	58.3	56.5	57.5	58.1	57.6	51.1	52.6	54.9	55.5	55.0	56.3	55.2	55.8	51.2	52.2	57.7	56.9	58.5	58.2	59.3	56.8

Also for the stressed scenario we compare the waiting lists obtained at the end of the simulated period by each of the planning policies with the initial waiting lists. Results are shown in Table 8, which reports results based on the same indicators $\mathcal{N}$, $\mathcal{T}$ and $\mathcal{R}$, similarly to Table 5.

This comparison mainly confirms the relative behavior of the policies observed in the base scenario, with an expected worsening of almost all indicators due to the congested situation.

Moreover, we want to perform a more detailed analysis for the two "critical" disciplines, namely GS (Table 9) and DS (Table 10). We adopt indicators $\mathcal{N}_s$, $\mathcal{T}_s$ and $\mathcal{R}_s$, having the same meaning of $\mathcal{N}$, $\mathcal{T}$ and $\mathcal{R}$ but referring only to the waiting list of discipline $s \in \{\text{GS}, \text{DS}\}$.

The results in Tables 9 and 10 show that even for DS and GS, fixed-MSS models (F_E and F_H) provide the worst performances in terms of average waiting and slack time of the surgeries in the list at the end of the simulation. When comparing the final length $\mathcal{N}_s$ of the waiting lists for the various policies, we must consider that while a large portion of cases in day surgery belong to class C, cases in general surgery are more balanced among the three classes. As a consequence, when using constrained models, GS is favored with respect to other disciplines, such as DS. This is particularly apparent for CEE|1-1, which is the policy that can most easily accommodate newly arrived cases in classes A and B. On the other hand, CEE|4-2 mitigates such effect on class C cases, still yielding very good results on classes A and B (of both disciplines). Note that, in the stressed scenario, the current (fixed) MSS still allows to be at pace with the demand of day surgeries, but appears dramatically undersized for general surgery (see first row of the two tables). These results suggest once more that a dynamic policy can be very useful, but it has to be accurately tuned according to the management goals and constraints.

Table 9: Comparison between initial and final waiting list for GS for each planning policy in the stressed scenario, for both objective functions f_1 and f_2

		I_{GS}	UEE		CEE|1-1		CEE|4-2		F_E		UHH		CHH|1-1		CHH|4-2		F_H		UHE		CHE|1-1		CHE|4-2	
			f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
GS_A	$\mathcal{N}_{GS}$	31.0	3.0	1.0	3.0	1.0	3.0	1.0	9.0	24.0	4.0	3.0	4.0	3.0	4.0	3.0	13.0	26.0	3.0	1.0	3.0	1.0	3.0	1.0
	$\mathcal{T}_{GS}$	95.3	4.7	0.0	4.7	0.0	4.7	0.0	17.1	31.5	7.0	4.7	7.0	4.7	7.0	4.7	21.0	33.9	4.7	0.0	4.7	0.0	4.7	0.0
	$\mathcal{R}_{GS}$	-65.3	25.3	30.0	25.3	30.0	25.3	30.0	12.9	-1.5	23.0	25.3	23.0	25.3	23.0	25.3	9.0	-3.9	25.3	30.0	25.3	30.0	25.3	30.0
GS_B	$\mathcal{N}_{GS}$	75.0	42.0	42.0	30.0	10.0	33.0	42.0	74.0	89.0	42.0	38.0	45.0	39.0	39.0	34.0	78.0	96.0	39.0	37.0	41.0	33.0	33.0	34.0
	$\mathcal{T}_{GS}$	157.5	12.2	12.2	7.2	0.0	8.5	12.2	27.9	36.3	12.2	10.5	13.7	10.9	10.9	8.9	30.1	40.3	10.9	10.0	11.8	9.5	8.5	8.9
	$\mathcal{R}_{GS}$	-97.5	47.8	47.8	52.8	60.0	51.5	47.8	32.1	23.7	47.8	49.5	46.3	49.1	49.1	51.1	29.9	19.8	49.1	50.0	48.2	50.5	51.5	51.1
GS_C	$\mathcal{N}_{GS}$	224.0	200.0	204.0	129.0	90.0	151.0	193.0	427.0	368.0	178.0	184.0	186.0	185.0	161.0	174.0	431.0	372.0	167.0	182.0	181.0	176.0	142.0	168.0
	$\mathcal{T}_{GS}$	179.7	31.9	32.4	20.1	13.9	23.7	30.7	69.0	59.2	28.1	29.1	29.5	29.3	25.2	27.5	69.7	59.9	26.4	28.7	28.6	28.1	22.1	26.5
	$\mathcal{R}_{GS}$	-89.7	58.2	57.6	69.9	76.1	66.3	59.3	21.0	30.8	61.9	60.9	60.5	60.7	64.8	62.5	20.3	30.1	63.6	61.3	61.4	61.9	67.9	63.5
GS_{tot}	$\mathcal{N}_{GS}$	330.0	245.0	247.0	162.0	101.0	187.0	236.0	510.0	481.0	224.0	225.0	235.0	227.0	204.0	211.0	522.0	494.0	209.0	220.0	225.0	210.0	178.0	203.0
	$\mathcal{T}_{GS}$	166.7	28.1	28.9	17.5	12.4	20.7	27.3	62.1	53.6	24.8	25.7	26.1	25.8	22.1	24.2	62.6	54.7	23.2	25.5	25.2	25.0	19.3	23.4
	$\mathcal{R}_{GS}$	-89.2	56.0	55.8	65.9	74.0	63.0	57.1	22.4	27.9	58.6	58.5	57.1	58.2	61.0	60.2	21.5	26.3	60.3	59.2	58.5	60.0	64.1	61.3

Table 10: Comparison between initial and final waiting list for DS for each planning policy in the stressed scenario, for both objective functions f_1 and f_2. Note that $\mathcal{T}_{DS}$ and $\mathcal{R}_{DS}$ are not defined when $\mathcal{N}_{DS} = 0$.

		I_{DS}	UEE		CEE|1-1		CEE|4-2		F_E		UHH		CHH|1-1		CHH|4-2		F_H		UHE		CHE|1-1		CHE|4-2	
			f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2	f_1	f_2
DS_A	$\mathcal{N}_{DS}$	3.0	0.0	0.0	1.0	2.0	1.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0
	$\mathcal{T}_{DS}$	51.7	–	–	7.0	14.0	7.0	–	–	–	7.0	7.0	7.0	7.0	7.0	7.0	–	–	7.0	–	7.0	–	–	–
	$\mathcal{R}_{DS}$	-21.7	–	–	23.0	16.0	23.0	–	–	–	23.0	23.0	23.0	23.0	23.0	23.0	–	–	23.0	–	23.0	–	–	–
DS_B	$\mathcal{N}_{DS}$	51.0	20.0	16.0	37.0	72.0	23.0	21.0	6.0	6.0	23.0	20.0	24.0	21.0	24.0	20.0	6.0	6.0	20.0	21.0	21.0	14.0	18.0	21.0
	$\mathcal{T}_{DS}$	140.9	7.0	6.1	19.3	42.3	8.8	8.3	0.0	0.0	11.6	7.7	11.4	9.0	11.4	7.7	0.0	0.0	7.0	8.3	7.7	5.0	5.8	8.3
	$\mathcal{R}_{DS}$	-80.9	53.0	53.9	40.7	17.7	51.2	51.7	60.0	60.0	48.4	52.3	48.6	51.0	48.6	52.3	60.0	60.0	53.0	51.7	52.3	55.0	54.2	51.7
DS_C	$\mathcal{N}_{DS}$	303.0	194.0	211.0	385.0	521.0	239.0	241.0	28.0	28.0	240.0	241.0	235.0	240.0	255.0	243.0	28.0	28.0	193.0	237.0	178.0	204.0	142.0	240.0
	$\mathcal{T}_{DS}$	174.1	20.0	22.2	44.2	61.8	25.7	25.9	0.0	0.0	25.7	25.9	25.1	25.7	27.6	26.1	0.0	0.0	19.9	25.4	18.1	21.4	13.3	25.8
	$\mathcal{R}_{DS}$	-84.1	70.0	67.8	45.8	28.2	64.3	64.1	90.0	90.0	64.3	64.1	64.9	64.3	62.4	63.9	90.0	90.0	70.1	64.6	71.9	68.6	76.7	64.2
DS_{tot}	$\mathcal{N}_{DS}$	357.0	214.0	227.0	423.0	595.0	263.0	262.0	34.0	34.0	264.0	262.0	260.0	262.0	280.0	264.0	34.0	34.0	214.0	258.0	200.0	218.0	160.0	261.0
	$\mathcal{T}_{DS}$	168.3	18.7	21.0	41.9	59.3	24.1	24.5	0.0	0.0	24.4	24.4	23.8	24.3	26.2	24.7	0.0	0.0	18.6	24.0	16.9	20.3	12.5	24.4
	$\mathcal{R}_{DS}$	-83.1	68.5	66.9	45.3	26.9	63.0	63.1	84.7	84.7	62.7	63.1	63.2	63.1	61.0	62.8	84.7	84.7	68.3	63.6	69.6	67.7	74.2	63.2

One final aspect which was investigated for the stressed scenario concerned the ability of the system to recover from the initial stress situation, in terms of waiting time and number of late cases. For each policy, Figures 2 and 3 show the average values of waiting time and, respectively, the number of late cases in the waiting lists at the end of each week. These values are compared with the values experimented by the hospital management in normal (i.e., not stressed) conditions, which are 60 days of waiting and 35 late cases (horizontal red lines in the graphs).

Almost all policies under study allow to recover from the initial stress condition. The two graphs show that the best policies require 11 to 15 weeks to recover from the stress condition; i.e., after such time all graphs in Figures 2 and 3 definitively remain below the red line. In particular, concerning waiting time, the behavior of all policies is similar, even if, once more, policies with fixed-MSS slightly underperform, especially in the last weeks of the observed period. Such underperformance of fixed-MSS policies is more apparent in terms of number of late cases. After an initial acceptably fast recovery, F_E and F_H significantly deviate from the reference and from the behavior of other policies. In fact, the initial fast recovery is due to the structure of the MSS as defined by the hospital management, which has a number of OR sessions devoted to DS and GS (see Figure 2, recall that in the stressed scenario cases from DS and GS have been added). 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.

5 Conclusions and future research

The main purpose of our study was to evaluate long-term policies in operating room planning, employing a variety of algorithmic tools, both heuristic and exact. We focused in particular on

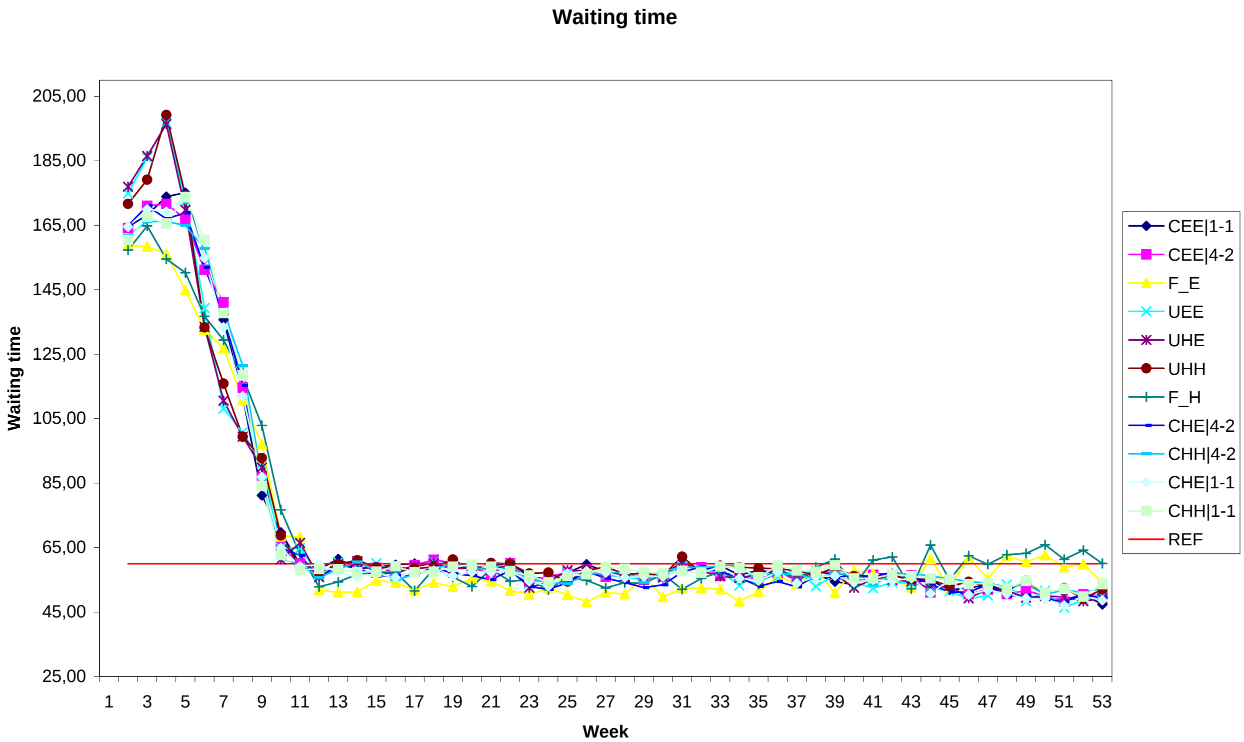

Figure 2: Waiting Time

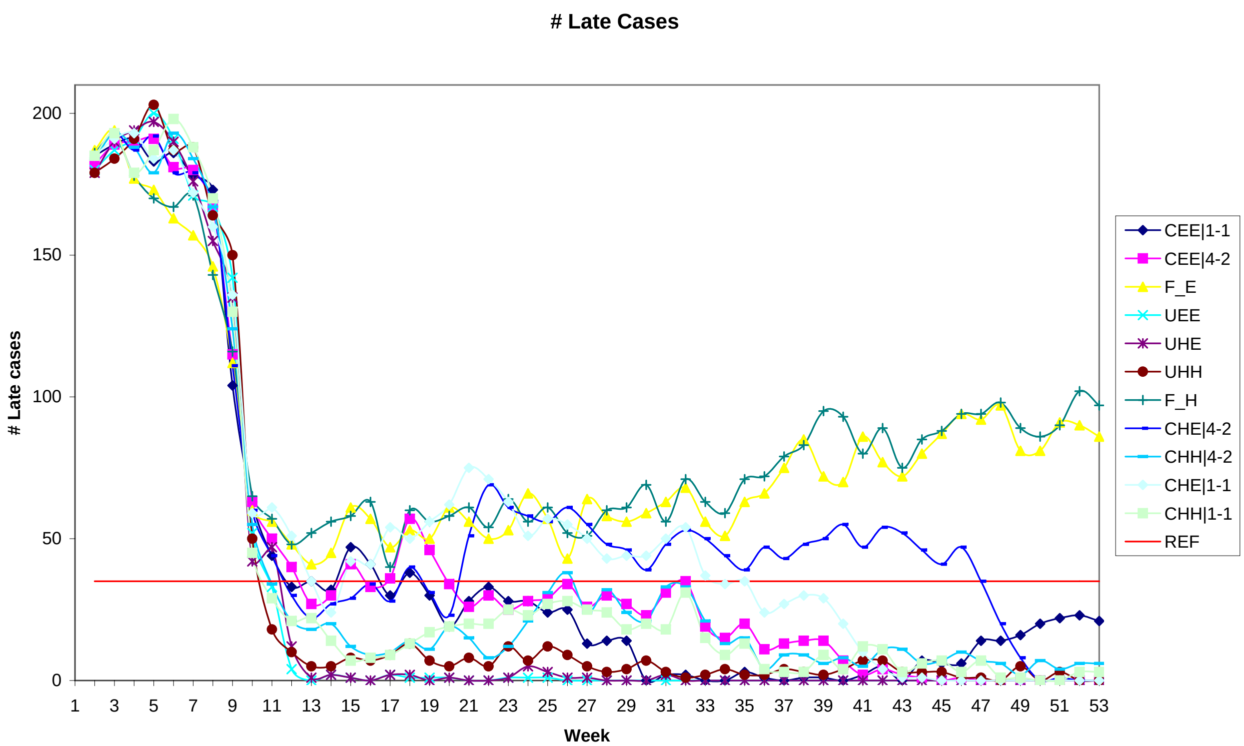

Figure 3: Number of Late Cases

the tradeoff between organizational complexity (stemming from a frequent and/or significant change in the MSS) 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 structure of the MSS can yield significant benefits, in terms of average waiting time and respect of due dates. The number and the frequency of OR session changes with respect to a reference MSS may become an element of negotiation which can actually help personnel to become more involved in such planning system. Of course, the hospital management must properly value the benefits vs. the organizational costs related to a given degree of flexibility, and our model may help in this assessment.

In our study we considered two objective functions. The first function implies that hospital management expresses a priority coefficient for each priority class; the second is only based on maximum allowed waiting times (as defined by regional laws). With the coefficients actually used by the management, we get similar results with both objective functions. This may suggest that, at least in certain cases, the coefficient assessment phase is not critical. This does not mean that one should use a completely predefined objective function, but rather that management can periodically revise coefficients on the basis of current system performance. This also depends on the ability of the staff to fruitfully interact with the planning system.

We also compared exact and heuristic approaches to MSSP and SCAP. Our results suggest that policies in which the MSS is generated heuristically and then filled on the basis of an exact combinatorial model ('·HE' policies) represent a good tradeoff between solution quality (always very close to the corresponding '·EE' policies) and computational effort, so that they are a valid tool to perform what-if analysis, or to recompute feasible plans in the face of unpredicted events.

Future research may address possible refinements and improvements of the models presented, such as:

- including detailed surgeons' timetables in the planning phase
- including uncertainties (e.g. in surgical case durations)
- adopt a multiobjective optimization approach, to explicitly account for more than one objective, besides what captured by the current objective functions.

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