

# Strategic performance assessment of master surgical schedule planning policies

A. Agnetis<sup>1</sup>, A. Coppi<sup>1</sup>, M. Corsini<sup>1</sup>, G. Dellino<sup>2</sup>, C. Meloni<sup>3</sup> and M. Pranzo<sup>2</sup>

<sup>1</sup> University of Siena, Italy

{agnetis,coppi,corsini,pranzo}@dii.unisi.it

<sup>2</sup> IMT Institute for Advanced Studies, Lucca, Italy

g.dellino@imtlucca.it

<sup>3</sup> Polytechnic of Bari, Italy

meloni@deemail.poliba.it

**Keywords:** elective surgery planning, master surgical schedule, operating room scheduling.

## 1 Introduction and problem formulation

The operating theater (OT) is one of the most critical resources in a hospital due to its strong impact on both health care costs and quality of service; see Hall (2006). Usually a single OT consists of several operating rooms (ORs), possibly with different characteristics, which may be shared by a number of surgical disciplines. In this study we focus on the allocation of elective surgeries only, without explicitly accounting for possible emergencies. In a given time period, the OT managers are faced with complex decision problems: at the tactical level, the Master Surgical Schedule Problem (MSSP) assigns surgical disciplines to OR sessions over time, thus obtaining the so-called MSS; then, at the operational level, the Surgical Case Assignment Problem (SCAP) consists in assigning elective surgeries to OR sessions, which determines the SCA. Recently several researchers have investigated OR planning and scheduling problems; see Cardoen *et al.* (2010) and Guerriero and Guido (2011) for comprehensive reviews. Several papers either focus on a single problem (e.g. Blake *et al.* (2002)) or address the two problems separately (e.g. Testi *et al.* (2007) use a sequential three-phase approach to determine the MSS, the SCA and the surgery sequencing). In other studies, MSSP and SCAP are concurrently addressed, either solving them to optimality through ILP formulations (Testi *et al.* 2008), or introducing heuristics to reduce problem size (Testi and Tanfani 2009). To our knowledge, no research papers have been focussing on elective surgery planning with a strategic perspective. In this context, our work mainly aims to 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 over the year. Our aim is therefore to test the advantages for the OT management to let the MSS vary throughout the year as compared with solving it once a year, as it is usually the case in most hospitals.

Computational experiments are based on real data from a medium-size public Italian hospital, in Empoli. Based on the characteristics of the OT in our case study, we consider a weekly schedule spanning five days, from Monday to Friday. OR sessions for elective surgery may last either half a day (morning and afternoon sessions) or the whole day (full-day session). No overtime is allowed, so the overall duration of the surgeries allocated to a given session cannot exceed the capacity of that session. However, to account for possible delays and/or uncertainties affecting surgery duration, we keep a planned slack time for each OR session, according to the hospital policies. A MSS may be subject to a number of restrictions. For instance, size and/or equipment constraints may require certain disciplines to be performed in specific ORs. Besides, every day a number of OR sessions

can be reserved to certain disciplines; this can also be used to enforce management of non-elective surgeries. Typically, the number of parallel OR sessions that can be assigned to the same discipline depends on the number of surgical teams available for that discipline. Moreover, workload balancing or other hospital management rules may bound the number of OR sessions assigned to each discipline in a week.

We formulate a mathematical programming problem to maximize the ORs utilization, accounting for the waiting time of case surgeries in the waiting lists. More specifically, we propose three alternative decision models, providing the MSS and the SCA for next week, and classified according to the MSS change policy; i.e., how the MSS can change over time. The *flexible MSS* model simultaneously solves MSSP and SCAP, letting the MSS potentially changing every week; the *bounded MSS* model identifies a MSS as a reference (upon the OT management’s suggestion), and solves MSSP and SCAP, such that the resulting MSS has a limited *distance* from the reference MSS, in terms of number of ORs for each day and session type assigned to different surgical disciplines across the two MSSs. Finally, the *stable MSS* model solves SCAP only, taking a given MSS as input, which is kept fixed throughout the year. Each of these models is solved to optimality using CPLEX. Furthermore, to reduce the possibly high computational costs for solving the mathematical models, we adopt a decomposition scheme addressing MSSP and SCAP sequentially. In particular, we solve the MSSP through the following heuristic: first, based on the waiting list of each surgical discipline, we derive a few sets of surgeries, such that each set can fit an OR session. So, for each discipline a set of *candidate* OR sessions is produced. Next, a complete surgical case assignment is temporarily produced selecting some of these candidate OR sessions. Finally, we discard all surgical cases, and only the MSS is retained. Such an MSS is the input to the next phase, which solves SCAP exactly, as a stable MSS model.

## 2 Case study and experimental setting

In this section we detail the characteristics of our real case study, based on the OT of a medium-size public Italian hospital, located in Empoli, and discuss the experimental setting. The OT is composed of six identically equipped ORs. Surgeries belong to the following disciplines: general surgery, otolaryngology, gynecology, orthopedic surgery, and urology. For modeling purposes, we consider day surgery as a discipline by itself: in fact, it consists of short surgeries only, so they can be managed more effectively than if accounted for together with ordinary surgeries.

The main input to the overall problem is the *waiting list* of each surgical discipline, containing all the patients that have to undergo surgery. Each entry of the waiting list specifies the patient personal record, the type of surgery, its priority level and expected duration (processing time, including setup times for cleaning and OR preparation for the next surgery), the date on which the patient entered the waiting list (entrance time), the days elapsed since the entrance time (waiting time), and the time within which the surgery should be performed (due date). We perform our simulations on alternative planning policies, as discussed in Section 1. We code the policies as ‘XY’, where ‘X’ denotes the MSS model (F = flexible, B = bounded, S = stable) and ‘Y’ specifies how MSSP is solved (E = exactly, H = heuristically, ‘\_’ (blank) when an MSS is given, so MSSP is not solved). For the bounded MSS model, we define a *block* as a time interval (weeks) during which the MSS remains fixed; changes in an MSS can occur only between the first week of the current block and the last week of the previous block, taken as reference MSS. The corresponding policy is coded as ‘B · $b$ - $\Delta$ ’, denoting a bounded model with a block time of  $b$  weeks and maximum distance  $\Delta$  between the MSSs of two consecutive blocks; ‘.’ specifies that the

code applies to both ‘Y’ = ‘E’ and ‘Y’ = ‘H’. In our tests, we adopt two alternative settings upon OT management’s suggestion, based on staff willingness to accept them; namely, one change per week ( $b = 1, \Delta = 1$ ) and two changes every four weeks ( $b = 4, \Delta = 2$ ). For the stable MSS model, we use the MSS currently adopted in the hospital, shown in Agnetis *et al.* (2011).

We simulate the system for 52 weeks and evaluate its performance under alternative planning policies, based 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 (1 t.s. = 15 minutes) 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) 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; (vi) max lateness: maximum lateness (days) among all surgical cases scheduled in the week; (vii) waiting time: waiting time (days) averaged over all surgical cases scheduled in the week; (viii) 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; (ix) 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–vi, and viii), patients’ safety and satisfaction (vii), ease of scheduling (ix).

### 3 Computational results and conclusions

Here we discuss the computational results obtained and draw some conclusions. The input of the first week of our simulation consists of the *real* waiting lists at the beginning of last year as provided by the hospital in Empoli. Throughout the simulated year, we update the waiting lists every week, deleting all surgeries performed in the current week and accounting for new surgery arrivals. We assume a random number of weekly arrivals, sampled from a uniform distribution centered around the average weekly arrival rate (190 patients), as estimated by OT managers. Then, new arrivals are obtained by resampling surgeries (with replacement) from the initial waiting list every week, thus guaranteeing to realistically reproduce the actual arrivals throughout the year.

**Table 1.** Performances of planning policies (averaged over 52 weeks)

	$\#$ cases	% empty t.s.	% empty t.s.*	$\#$ late cases	mean lateness (days)	max lateness (days)	waiting time (days)	mean tardiness (days)	computing time (s)
FE	194	0.05	0	24	-16	5	57	7	1692
FH	193	0.05	0	25	-15	7	58	7	34
BE 1-1	191	0.27	0	38	-16	23	67	13	558
BH 1-1	193	0.05	0	29	-16	13	58	7	40
BE 4-2	193	0.08	0	35	-16	18	58	7	150
BH 4-2	193	0.08	0.01	33	-16	17	57	7	42
S_	184	0.45	0.36	65	-14	41	61	13	42

Table 1 reports the results for the scenario described so far. All the policies schedule a similar number of surgical cases, except for the stable MSS model (S\_), which — on average — schedules 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 flexible and bounded policies fill OR sessions almost perfectly, with less than 45 minutes empty sessions across the ORs in the whole week;  $S_{-}$  performs slightly worse, also in terms of empty time slots due to empty waiting lists (third column). In fact, keeping the MSS fixed, when one or more waiting lists have been emptied, the corresponding OR sessions cannot be assigned to other disciplines, thus remaining empty. This 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 bounded MSS models is significantly better than  $S_{-}$  and only slightly worse than flexible MSS models. This is true for both  $B_{-}|4-2$  and  $B_{-}|1-1$ , with no clear dominance between them. This suggests that a small amount of flexibility in the definition of the weekly MSS appears as extremely beneficial, cutting figures such as the average number of late cases and maximum lateness by about one half. To further support the choice of the planning policy to be implemented in the OT, we compute the distance between the MSSs of two consecutive weeks as determined by the flexible models: the average distance is 12.5 OR sessions, varying between 5 and 37 throughout the year. This implies that on average the flexible MSS model changes 20% of the whole MSS every week, with a worst case of 67%. On the other hand, the bounded 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, while the difference in the maximum lateness and mean tardiness is more evident. As expected, the policies solving MSSP exactly require the highest computing time. For a given MSS model (thus keeping ‘X’ fixed), solving MSSP exactly guarantees the best quality in terms of the selected performance indicators. On the other hand,  $\cdot H$  policies spend a reasonable computing time to solve MSSP and SCAP, keeping the quality of the corresponding solutions satisfactory.

## Acknowledgements

The research is partially supported by the grant “Gestione delle risorse critiche in ambito ospedaliero” (“Critical resource management in hospitals”) of the Regione Toscana - PAR FAS 2007-2013 1.1.a.3.- B51J10001140002.

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