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Addressing Conflicting Stakeholders' Priorities in Surgical Scheduling by Goal Programming.

PAOLA CAPPANERA
University of Florence
Dipartimento di Ingegneria dell'Informazione
IBIS Lab.
PO Box 50139, Via Santa Marta 3, Florence, Italy

FILIPPO VISINTIN*
University of Florence
Dipartimento di Ingegneria Industriale
IBIS Lab.
PO Box 50134, Viale Morgagni 40/44, Florence, Italy

AND

CARLO BANDITORI
University of Florence
Dipartimento di Ingegneria Industriale
IBIS Lab.
PO Box 50134, Viale Morgagni 40/44, Florence, Italy

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*corresponding author

Abstract

In this study, we propose a mixed integer multi-objective model which allows determining the number and typology of surgeries to be scheduled in each OR, day and session of a multiple day planning period, in context where each OR session of the planning horizon *has already been assigned* to a specialty, with the (multiple) objective of obtaining a *desired:* (i) patient due date fulfilment rate, (ii) OR utilisation, (iii) bed utilisation, (iv) number of scheduled surgeries. These objectives, reflect heterogeneous priorities of different stakeholders of the surgical scheduling process. To address the described multi-objective problem, we use a goal programming approach and we show how the exploration of the weight space, typical of such approach, can be more efficient if informed by a correlation analysis. The results presented in this study are based on real data from the Meyer University Children's Hospital in Florence.

1 Introduction

An ever growing number of hospitals considers performance improvement of their operating theatre (OT) as a top priority. OT, in fact, drives most of the hospitals' revenues and costs (Denton et al. 2007; Cardoen et al. 2010) and its operations are tightly linked with those of other departments. Optimising the OT operations requires, first and foremost, addressing the so-called surgical scheduling problem. This problem entails the selection of the surgical procedures to be performed in a given time horizon, the allocation of time and Operating Room (OR) capacity to those procedures, and the sequencing of the procedures within the allocated time (May et al. 2011).

Because of its complexity, such a problem is usually decomposed in three sub-problems that are solved in cascade: (1) the case-mix planning, i.e. the determination, usually on a yearly basis, of the total amount of OR time to assign to each surgical specialty, (2) the master surgical scheduling, i.e. the determination of the specialty or specialties to assign to each OR, day and session of the planning horizon (typically 2 weeks or 1 month), and finally (3) the patients selection and sequencing.

However, in recent studies, decisions characterising surgical scheduling-related problems traditionally solved separately, have been successfully integrated. As an example, (Santibáñez et al. 2007; Banditori et al. 2013; Cappanera et al. 2014; Visintin et al. 2016) show that is viable determining jointly the specialty to assign to each session of the planning horizon (decision typical of the master surgical scheduling problem) and the number and typology of surgeries to perform in each session (decision typical of the patient selection problem). Other authors, instead, develop joint models to solve, for example, surgical case scheduling and staff rostering problems (Huele & Vanhoucke 2014, Wang et al. 2015, Guo et al. 2016).

Another distinguishing feature of the surgical scheduling problem is its multi-objective nature. Solving this problem, in fact, inherently requires taking into consideration multiple stakeholders such as top managers, OR personnel (surgeons, anaesthetists, nurses), bed managers and patients, whose priorities are often conflicting (Glauberman & Mintzberg 2001). Hospital top management, for example, tends to focus on maximising the number of surgeries scheduled. Scheduling a high number of surgeries, in fact, allows increasing the hospital revenues and reducing average patient wait time. The maximisation of the scheduled surgeries, however, may lead to peaks in the daily utilisation of ORs and beds. This conflicts with the desiderata of OR personnel and bed managers. The OR personnel, in fact, expects the OR workload to be evenly balanced across sessions to avoid overtime work and the risk associated with excessively busy sessions. Similarly, bed managers, are interested in avoiding peaks in the utilisation of beds, since overcrowding can cause risks, schedule disruptions and the relocation of patients already hospitalised. Patients, in their turn, want to wait a fair amount of time before being treated. This, especially in those countries where the health care system is based on the principle of universal coverage and financed by general taxation, has encouraged policy makers to set specific targets in terms of Maximum Time Before Treatment (MTBT) and to monitor the due-date fulfillment rate (see, for example, Ministero della Salute, 2010 and Canadian Association of Radiologists, 2013). Matching the patients' due dates, however may reduce the number of cases that is possible to schedule and create problems in term of OR and bed balancing.

The complex and multi-stakeholder nature of the surgical scheduling problems has encouraged the development of multi-objective models (Banditori et al. 2013, Rachuba & Werners 2014, Meskens et al. 2013).

Unfortunately, considering multiple objectives while addressing jointly decisions at multiple levels, can result in problems characterised by high computational complexity and, thus, in models that might not be solved on real instances. Possible ways to manage such a complexity consist in treating one or more of the criteria as constraints, as it happens in (Aringhieri et al. 2015), in reducing the length of the planning horizon in which the decisions have to be taken (Ozkarahan 2000), or in trading-off the type of decisions to take concurrently and the number of objectives to consider.

In this study, we adopt this latter approach. Specifically, we address the problem of determining the *number* and *typology* of surgeries to be scheduled in each OR, day and session of a multiple day planning period (i.e. 2 weeks), in context where each session of the planning horizon *has already been assigned* to a specialty, with the (multiple) objective of obtaining a *desired:* (i) patient due date fulfilment rate, (ii) OR utilisation, (iii) bed utilisation, (iv) number of scheduled surgeries. To address this problem, we assume that surgical cases in the hospital waiting list are organised into *surgery groups* (Santibáñez et al. 2007; Banditori et al. 2013), i.e., into homogeneous groups of cases characterised by the same specialty and by similar expected surgical time (ST) and expected length of stay (LoS). Hence, we propose a multi-objective MIP model whose solution indicates, for each OR session of the planning horizon, the number of surgeries to perform and the surgery groups these surgeries must belong to. It is worth to notice that the hypothesis of assuming specialty-session assignment as fixed, while limiting the computational complexity of the model, reflects a managerial practice that is shared by many hospitals (Agnetis et al. 2012; Visintin et al. 2016). Working with a fixed specialty-session assignment, in fact, allows specialists/surgical teams to know in advance the days of the week when they will be needed in the OR, thereby making it easier for them to plan their multiple activities within and outside the hospital.

To address the mentioned multi-objective model, we use a goal programming approach where the exploration of the weight space is based on an algorithm taken from the literature (Jones & Tamiz 2010) and information coming from a correlation analysis, based on the Spearman's rank correlation coefficient, are used to limit the combinations of weights to explore thus allowing a gain in efficiency. This is consistent with (Jones 2011) who suggests that preferential information may be used to limit the search in the weight space.

This study has thus a threefold aim:

- Presenting a novel surgical scheduling optimisation model;
- Presenting an approach where a classical algorithm proposed in the goal programming literature to explore the weight space is complemented with a correlation analysis;
- Showing the results achieved by using the presented model and approach on real data.

The remainder of the paper is organised as follows: in Section 2, we provide a brief review of the literature. In Section 3, we describe, in detail, the optimisation problem addressed. The optimisation model is then presented in Section 4. In Section 5, we present the empirical results and in Section 6 we discuss them. Subsequently, in Section 7, we draw the conclusions and present the study's limitations.

2 Literature review

As observed in the Introduction, in addition to advocate the use of joint approaches, the literature suggests that the conflicting priorities of the stakeholders make the surgical scheduling problem inherently multi-objective (Banditori et al. 2013, Aringhieri & Duma 2015; Duma & Aringhieri 2015) and consequently proposes several models and algorithms to address it. In (Adan & Vissers 2002) the objective function minimises the deviation of the resources' utilisation from fixed targets. Specifically, the model takes into consideration the ORs, two types of beds, i.e. medium and intensive care, and intensive care ward nurses. Guinet & Chaabane (2003) propose a primal-dual heuristic to address the problem of assign patients to ORs on a weekly planning horizon. The criteria considered are patient satisfaction, measured by number of days patients wait in the hospital, and resource efficiency, measured by overtime. Jebali et al. (2006), instead, develop a two-phase integer programming-based approach where the first phase addresses the surgery assignment problem with the objective of minimising hospitalisation, undertime and overtime costs. At the second phase the objective consists in minimising the total overtime cost for ORs and decisions taken in the first phase may be possibly reconsidered. Van Oostrum et al. (2008), on their turn, propose a bi-criteria optimisation model in which the objective function minimises the OR capacity and levels the bed occupation over the planning horizon. In addition to bed levelling, the objective function in (Beliën et al. 2009) aims to reduce the number of ORs shared by different surgical specialties and to make the schedule as much repetitive as possible. Cardoen et al. (2009), instead, study a multi-objective surgical case sequencing problem where the objectives are combined together in a weighted function which takes into account how each criterion ranks in the range between the best and the worst values it can assume when considered alone on the given patient population. Meskens et al. (2013) address the daily multi-objective operating room scheduling where the objectives consist in minimising the makespan, minimising overtime hours and maximise affinities among members of the surgical team while taking into account their desiderata by means of constraint programming. Rachuba & Werners (2014) propose a MIP model in which the objective function considers the patients waiting time, the OR overtime and the number of patients that must be deferred to the next planning horizon because of lack of capacity. We conclude the section with a brief review of studies that propose goal programming approaches for surgical related scheduling problems. As anticipated in the Introduction, goal programming is in fact, a widely used methodology to address multi-objective problems. Blake & Carter (2002) propose the use of goal-programming for a resource allocation problem arising in a health care setting; there, the aim is to support hospital decision makers and physicians to determine the mix and the volume of the cases they treat. Ogulata & Erol (2003) address a three-stage surgical problem where the stages are: (i) selection of patients, (ii) assignment of patients to surgeon groups, and (iii) scheduling of patients in the weekly planning horizon. Goal programming is used in all of the three stages and the criteria considered are the utilisation of operating room capacity, patient waiting time, and a balanced distribution of workload among surgeon groups. Ozkarahan (2000) uses goal programming for the assignment of surgeries to OR in a one-day planning horizon. Block scheduling is considered and the total time allocated to each specialty in each day is known in advance. Specialties provide their lists of planned surgeries, ordered by urgency, to the personnel in charge of scheduling and they may specify the OR they would like to use for each procedure; lists may also include extra cases. Target values are given for: (i) time allocated to each specialty, (ii) total available time of each OR, (iii) total number of OR preferences made by each specialty, (iv) total weight of listed surgeries (to assure that only surgeries with small weights are possibly postponed), (v) number of ICU beds available. Alternative functions are also considered to control nurses' dissatisfaction. The problem addressed in (Ozkarahan 2000) is thus similar to the one this study focuses on, the main difference being the length of the planning horizon.

It is worth to observe that the use of correlation analysis - and in particular the use of non-parametric coefficient, such as the Spearman's one - in conjunction with goal programming is not new. However, to the best of our knowledge, no studies use a correlation analysis to refine the search in the weight space. Instead, correlation analyses are typically used to: measure the correlation between single criterion measures and aggregated measures (Garcia et al., 2010); cross-validate common weight sets in DEA studies (Makui et al., 2008, Alinezhad & Kiani Mavi, 2009; Lam 2010; Zohrehbandian et al., 2010); compare alternative preference decomposition procedures (Lam & Choo, 1995).

In sum, despite efficiency, resource balancing and patients' priorities are by no means novel optimisation criteria used in OR planning and scheduling problems, to the best of our knowledge, no model integrates all of them on a multiple-day planning horizon. To address this gap, in this study we propose a goal programming model and advocate the use of correlation analysis to take informed decisions on how to set the weights in the model's objective function.

3 Problem addressed

In this study we assume that patients in the hospital waiting lists are characterised by four attributes: surgery group, priority class (and the associated MTBT), latest due-date (LDD) and earliest programmable date (EPD). As pointed out in the Introduction, patients associated with the same surgery group are characterised by the same specialty and the same expected ST and LoS. The ST is expressed in multiple of 30 minutes (e.g. ST=30, means that the surgeries within the group are expected to last less than 30', ST=60 means that they are expected to last from 30 to 60', etc.). The LoS, instead, is expressed in days. The EPD indicates the day starting from which the patient can be scheduled. In general, it can differ from the day when the surgery was prescribed (those patients whose EPD precedes the first day of the planning horizon are considered eligible to be scheduled from the beginning of the planning horizon). The priority class (A, B, C), indicates the number of days within which patient should be scheduled (respectively, 30, 60, 90 days), starting from the EPD. Finally, the LDD, is calculated considering the EPD and the assigned priority class (e.g., for Class A patients, LDD=EPD + 30 days).

We consider three critical resources, namely ORs, beds, and surgeon teams and we assume that each surgery requires the simultaneous availability of all of these resources to be scheduled. ORs are considered as interchangeable, i.e. they are not dedicated to specific surgery groups nor contain special equipment. OR time is slotted in sessions lasting half day (morning or afternoon session) or the whole day (daily session). Beds are organised in different units. The specific unit where a patient is hospitalised after surgery depends on her/his surgery group. Surgeons teams, are associated with one surgical specialty. Surgical specialties are assigned to OR sessions a priori by means of an *allocation grid*. Such a grid indicates, for each day of the planning horizon, the specialty assigned to each OR and session. We assume that if a specialty is assigned to an OR session, then there will be always a surgeon team of that specialty available in that session. Considering these hypotheses, we address the problem of determining for each OR session in the planning horizon, the number of cases to schedule and the surgery group of each case, with the aim of:

- scheduling a *target* number of patients with LDD expiring in the planning horizon;
- obtaining a *target* utilisation of the ORs;
- obtaining a *target* utilisation of the bed units;
- scheduling a *target* number of surgeries.

4 Model description

To address the problem presented in the previous section, we formulated a mixed integer goal-programming model. The model comprises the following sets and parameters:

S	set of surgical specialties
K	set of surgery groups
O	set of ORs
D	set of days in the planning horizon
$D_1, \ldots, D_e$	sets of extra time periods outside the planning horizon
T	set of sessions
B	set of bed units
P	set of patients' priority classes
I	set of criteria
G_{sodt}	the allocation grid, equal to 1 if surgeries belonging to the specialty s can be performed in OR o, on day d, in session t, 0 otherwise
H_{odt}	available time of OR o on day d, time slot t
s_k	specialty of surgery group k
γ_k	expected ST of surgery group k

α_k expected LoS after surgery required by group k

β_k expected LoS before surgery required by group k

R_{bd} number of beds in unit b available on day d

E_{kd} number of cases in surgery group k, whose EPD is on day d

e number of time periods preceding and following the planning horizon

L_{pd} number of cases of priority p whose LDD is on day d, $\forall p \in P, \forall d \in D \cup D_1 \cup ... \cup D_e$

$\hat{q}$ target value for the OR utilisation rate

$\hat{r}$ target value for the bed utilisation rate

$\hat{n}_i$ target value for the objective i

w_{pj} penalty associated with cases of priority p with LDD in D_j not scheduled in the planning horizon, $\forall p \in P, \forall j \in 1..e$

W_i weight associated with objective i.

Let us introduce the decision variables:

y_{kpodt} number of procedures of surgery group k with priority p assigned to OR o on day d in session t

and the following auxiliary variables:

z_{bd} number of beds of type b occupied on day d

q_{odt} utilisation rate of OR o, on day d, in session t

r_{bd} utilisation rate of beds in unit b on day d

u_{pj} number of cases with priority p and with LDD in time period D_j not scheduled in the planning horizon, $\forall p \in P, \forall j \in 0..e$ where j=0 refers to D, i.e. D_0=D

q^+_{odt} positive deviation of the utilisation rate of OR *o*, on day *d*, in session *t* from the fixed target

q^-_{odt} negative deviation of the utilisation rate of OR *o*, on day *d*, in session *t* from the fixed target

r^+_{bd} positive deviation of the utilisation rate of beds in unit *b* on day *d* from the fixed target

r^-_{bd} negative deviation of the utilisation rate of beds in unit *b* on day *d* from the fixed target

n_i value associated with objective *i*

$\overline{n}_i$ deviation (positive or negative) of objective *i* from the fixed target.

Since the allocation grid is fixed in input through the parameter G_{sodt}, the surgery groups that can be scheduled in a given OR *o*, on a given day *d* in the time slot *t* are restricted to the ones belonging to the surgical specialty *s* for which the parameter G_{sodt} is equal to 1. For this reason, variables *y* are defined on a subset of the set $(K \times P \times O \times D \times T)$. Specifically, we introduce, for each surgery group *k*, the set A_k that is a collection of triples (*o*,*d*,*t*) indicating, the OR sessions, in which the surgery group *k* can be scheduled. More formally, if s_k denotes the specialty of surgery group *k*, A_k are defined as follows:

$$A_k = \{(o,d,t) \ s.t. \ o \in O, d \in D, t \in T \ and \ G_{s_k odt} = 1\}.$$

Variables y_{kpodt} are thus defined $\forall k \in K, \forall p \in P, \forall (o,d,t) \in A_k$. Given these sets, parameters and variables, the model is formulated as follows:

$$\sum_{\substack{k \in K, p \in P: \\ (o,d,t) \in A_k}} \gamma_k y_{kpodt} \le H_{odt} \qquad \forall o \in O, \forall d \in D, \forall t \in T \tag{4.1}$$

$$\sum_{\substack{k \in K, p \in P, o \in O, \\ t \in T:(o,d,t) \in A_k}} \sum_{d'=\max(1,d-\alpha_k)}^{\min(|D|,d+\beta_k)} y_{kpod't} = z_{bd} \qquad \forall b \in B, \forall d \in D \tag{4.2}$$

$$z_{bd} \le R_{bd} \qquad \forall b \in B, \forall d \in D \tag{4.3}$$

$$q_{odt} = \frac{\sum_{\substack{k\in K,\, p\in P:\\ (o,d,t)\in A_k}} \gamma_k y_{kpodt}}{H_{odt}} \qquad \forall o \in O, \forall d \in D, \forall t \in T \tag{4.4}$$

$$r_{bd} = \frac{z_{bd}}{R_{bd}} \qquad \forall b \in B, \forall d \in D \tag{4.5}$$

$$\sum_{\substack{p\in P, o\in O, d'\in D: d'\le d,\\ t\in T:(o,d',t)\in A_k}} y_{kpod't} \le \sum_{d'\in D: d'\le d} E_{kd'} \qquad \forall k \in K, \forall d \in D \tag{4.6}$$

$$\sum_{\substack{k\in K, o\in O, d\in D,\\ t\in T:(o,d,t)\in A_k}} y_{kpodt} + \sum_{h=0}^{j} u_{ph} \ge \sum_{d\in D\cup D_1\cup\ldots\cup D_j} L_{pd} \qquad \forall p \in P, \forall j \in 0..e \tag{4.7}$$

$$q^+_{odt} \ge q_{odt} - \hat{q} \qquad \forall o \in O, \forall d \in D, \forall t \in T \tag{4.8}$$

$$q^-_{odt} \ge \hat{q} - q_{odt} \qquad \forall o \in O, \forall d \in D, \forall t \in T \tag{4.9}$$

$$r^+_{bd} \ge r_{bd} - \hat{r} \qquad \forall b \in B, \forall d \in D \tag{4.10}$$

$$r^-_{bd} \ge \hat{r} - r_{bd} \qquad \forall b \in B, \forall d \in D \tag{4.11}$$

$$n_1 = \sum_{p\in P, j\in 0..e} w_{pj} u_{pj} \tag{4.12}$$

$$n_2 = \sum_{\substack{o\in O, d\in D,\\ t\in T}} q^+_{odt} + q^-_{odt} \tag{4.13}$$

$$n_3 = \sum_{b\in B, d\in D} r^+_{bd} + r^-_{bd} \tag{4.14}$$

$$n_4 = \sum_{\substack{k\in K, p\in P, o\in O,\\ d\in D, t\in T:(o,d,t)\in A_k}} y_{kpodt} \tag{4.15}$$

$$\bar{n}_1 \geq n_1 - \hat{n}_1 \tag{4.16}$$

$$\bar{n}_2 \geq n_2 - \hat{n}_2 \tag{4.17}$$

$$\bar{n}_3 \geq n_3 - \hat{n}_3 \tag{4.18}$$

$$\bar{n}_4 \geq \hat{n}_4 - n_4 \tag{4.19}$$

$$y_{kpodt} \in \mathrm{N} \qquad \forall k \in K, \forall p \in P, \forall (o,d,t) \in A_k \tag{4.20}$$

$$u_{pj} \geq 0 \qquad \forall p \in P, \forall\ j \in 0,\ldots,e \tag{4.21}$$

$$z_{bd} \geq 0,\ r_{bd}^{+} \geq 0,\ r_{bd}^{-} \geq 0 \qquad \forall b \in B, \forall d \in D \tag{4.22}$$

$$q_{odt}^{+} \geq 0,\ q_{odt}^{-} \geq 0 \qquad \forall o \in O, \forall d \in D, \forall t \in T \tag{4.23}$$

$$\bar{n}_i \geq 0 \qquad \forall i \in I \tag{4.24}$$

$$\min \sum_{i \in I} \frac{W_i \bar{n}_i}{\hat{n}_i} \tag{4.25}$$

Constraints (4.1) assure that for each OR session, the sum of the STs of the scheduled surgeries does not exceed the available time. Constraints (4.2) compute the number of utilised beds for each unit and for each day of the planning horizon. Constraints (4.3) limit the number of occupied beds. Constraints (4.4) and constraints (4.5) compute respectively the daily utilisation of the OR sessions and of the different bed units. Constraints (4.6) assure that the number of scheduled surgeries for each group does not exceed the number of cases that are available, depending on the relevant EPDs. Constraints (4.7) allow for the respect of the LDDs' of the patients in the waiting list. Specifically, these covering constraints impose that the number of scheduled surgeries of a given priority p should be greater or equal than the number of cases in the waiting lists belonging to that priority. If this cannot happen the corresponding variable u, which measures the number of not scheduled surgeries of priority p and with a LDD falling in the planning horizon D or in some extra time period D_j with $j=1,..,e$, assumes a value greater than zero. The sum of the u variables is penalised in the objective n_1 according to the priority and the tardiness.

Constraints (4.8) and (4.9) compute positive and negative deviations of OR utilisation from the fixed target, for each triple (o,d,t). Constraints (4.10) and (4.11) are their counterparts for the bed unit utilisation. Constraints (4.12)-(4.15) compute the values of the four objectives: specifically, constraint (4.12) computes the weighted sum of the penalties associated with the missed scheduling of the patients with certain LDDs and priorities; constraints (4.13) and (4.14) calculate the sum of the deviations from the fixed targets respectively of ORs and bed units; constraint (4.15) computes the number of scheduled surgeries. Constraints (4.16)-(4.19) compute, for each objective the positive or negative deviation from the fixed target. The remaining constraints define variable domains. The weighted sum of the deviations calculated in constraints (4.16)-(4.19) is minimised in the objective function (4.25).

5 Analysis

5.1 Input data

The experimental campaign presented in this study is based on real data from the Meyer University Children's Hospital in Florence (hereafter Meyer Hospital). Such an hospital is characterised by:

- a planning horizon of 2 weeks;
- 11 surgical specialties;
- 4 interchangeable ORs dedicated to elective surgeries;
- 3 bed units, i.e. day surgery, week hospital and ordinary unit. Each unit has a capacity of 14 beds. Day hospital unit accommodates patients with LoS equal to one day;
- target daily utilisations of 85% for both OR sessions and bed units;
- a waiting list organised in approximately 170 surgery groups.

In this study, we used 30 different waiting lists as input data. These waiting lists were obtained sampling the actual hospital waiting list 30 times in a period spanning from January 2014 and December 2015. For each list, we clustered cases according with their LDDs. Specifically, we identified 4 groups of cases:

- cases with LDD in D (D_0 in model description);
- cases whose LDD expired in the two weeks preceding D (D_1 in model description);
- cases whose LDD expired before the two weeks preceding D (D_2 in model description);
- cases with LDD expiring after D (D_e=D_3 in model description, i.e. the number e of extra time periods is equal to 3).

The weights w_{pj} in the objective n_1 were assigned in a way that prioritises, respectively, cases with higher priority and cases belonging to groups with a lower rank (group 1 has the highest priority, group 4 the lowest).

The weights W_i in the objective function, instead, were calculated using the (Jones & Tamiz 2010) algorithm. This algorithm allows systematically exploring the weight space and it is based on two parameters: *Tmax* and *max_level*. The former represents the max number of weights to be varied simultaneously, while the latter indicates the level of granularity to use in the exploration of the weight space. The exploration of the weight space was performed in two stages:

- in the first stage, we fixed *Tmax*=3 and *max_level*=1 and initialized the algorithm with the weights (0.25, 0.25, 0.25, 0.25) thereby obtaining 29 unique weight combinations (see Table 2).
- in the second stage, we refined the weight space exploration increasing the *max_level* parameter from 1 to 3, thereby obtaining additional 56 unique weight combinations.

Finally, the targets for the different objectives were identified involving the hospital's bed manager, OR manager and medical director in an open discussion. After some negotiations these stakeholders agreed on the following set of targets:

- $\hat{n}_1$ *=15%,* this target is set in a way that at least 85% of the patients (weighted to take into consideration their priority class) with LDD in the planning horizon should be scheduled in the planning horizon,
- $\hat{n}_2$ *=10%,* i.e. the mean daily deviations of the OR utilisation from the target (85%) should be less than 10%
- $\hat{n}_3$ *=5%,* i.e. the mean daily deviations of the daily BED utilisation from the target (85%) should be less than 5%
- $\hat{n}_4$ *=240* i.e. the number of surgery scheduled should not be smaller than 240 (i.e. negative deviations are penalised).

For each sampled waiting list, we solved the model in correspondence with each combination of weights thereby resulting in 2550(=30*85) problem instances. The computational campaign was performed on a PC equipped with an Intel iCore 7 @3.40 GHz processor and 32 GB of RAM. We set a time limit of 60 seconds for each instance.

To facilitate the analysis of the results, in Table 1 we report a short description of each objective and introduce an intuitive abbreviation that will be used in the remainder of the paper.

Table 1 Objectives description

Obj (i)	**Description**	**Label**
1	scheduling a *target* number of patients with LDD expiring in the planning horizon	oLDD
2	obtaining a *target* utilisation of the ORs	oOR
3	obtaining a *target* utilisation of the BED units	oBED
4	scheduling a *target* Number of Surgeries	oNS

5.2 Results

This section is organised in two parts. First we show the results achieved applying the model presented in the previous section to the Meyer Hospital's data, using a first batch of 29 weight combinations calculated using the Jones & Tamiz (2010)'s algorithm. Then we will refine the exploration of the weight space using the results of a correlation analysis in conjunction with the mentioned algorithm.

5.2.1 Exploration of the first batch of weight combinations

Table 2 shows for each combination of weights *c*, and for each objective *i*, the value of the weight W_i and the *acceptance rate* AR_i of the model's solutions. AR_i represents the percentage of instances for which the model returned a solution meeting the target $\hat{n}_i$ (e.g. AR_i*=100%* means that the model solution met the target $\hat{n}_i$ for all the 30 tested waiting lists). The last column identifies with an asterisk a not dominated weight combination (e.g. c=2) or a weight combination dominating the one corresponding to the row considered (e.g. c=1 is dominated by c=6). Combination *p* dominates combination *q* if *p* is not worse than *q* on all the criteria but one, and there exists at least one criterion for which *p* is better than *q*.

Table 2 Combinations of weights and acceptance rates

c	W_1	W_2	W_3	W_4	AR_1	AR_2	AR_3	AR_4	Dom
1	0.250	0.250	0.250	0.250	83.3%	93.3%	100.0%	93.3%	6
2	0.990	0.003	0.003	0.003	90.0%	86.7%	90.0%	83.3%	*
3	0.620	0.127	0.127	0.127	83.3%	90.0%	93.3%	93.3%	6
4	0.003	0.990	0.003	0.003	76.7%	100.0%	100.0%	83.3%	8
5	0.127	0.620	0.127	0.127	76.7%	100.0%	100.0%	86.7%	8
6	0.003	0.003	0.990	0.003	83.3%	96.7%	100.0%	96.7%	*
7	0.127	0.127	0.620	0.127	83.3%	93.3%	100.0%	96.7%	6
8	0.003	0.003	0.003	0.990	80.0%	100.0%	100.0%	100.0%	*
9	0.127	0.127	0.127	0.620	80.0%	100.0%	100.0%	100.0%	*
10	0.495	0.495	0.005	0.005	86.7%	100.0%	93.3%	80.0%	*
11	0.373	0.373	0.128	0.128	83.3%	100.0%	100.0%	86.7%	*
12	0.495	0.005	0.495	0.005	90.0%	93.3%	100.0%	80.0%	*
13	0.373	0.128	0.373	0.128	80.0%	93.3%	100.0%	83.3%	20
14	0.495	0.005	0.005	0.495	86.7%	90.0%	90.0%	100.0%	24
15	0.373	0.128	0.128	0.373	83.3%	96.7%	100.0%	96.7%	*
16	0.005	0.495	0.495	0.005	80.0%	100.0%	100.0%	86.7%	20
17	0.128	0.373	0.373	0.128	76.7%	100.0%	100.0%	90.0%	8
18	0.005	0.495	0.005	0.495	76.7%	100.0%	96.7%	100.0%	8
19	0.128	0.373	0.128	0.373	76.7%	96.7%	100.0%	96.7%	8
20	0.005	0.005	0.495	0.495	80.0%	100.0%	100.0%	100.0%	*
21	0.128	0.128	0.373	0.373	80.0%	93.3%	100.0%	100.0%	20
22	0.330	0.330	0.330	0.010	80.0%	93.3%	100.0%	83.3%	11
23	0.290	0.290	0.290	0.130	80.0%	100.0%	100.0%	80.0%	11
24	0.330	0.010	0.330	0.330	86.7%	90.0%	100.0%	100.0%	*
25	0.290	0.130	0.290	0.290	83.3%	96.7%	100.0%	90.0%	15
26	0.010	0.330	0.330	0.330	76.7%	100.0%	100.0%	100.0%	8
27	0.130	0.290	0.290	0.290	80.0%	96.7%	100.0%	96.7%	6
28	0.330	0.330	0.010	0.330	86.7%	100.0%	83.3%	100.0%	*
29	0.290	0.290	0.130	0.290	80.0%	96.7%	96.7%	86.7%	25

Looking at Table 2 it is possible to observe that:

i) There is no combination of weights that allows meeting the target $\hat{n}_1$ for all the 30 instances. For the other objectives (i=2,3,4) it is possible to obtain *AR=100%* respectively for 13/29 22/29, 9/29 weight combinations. The mean acceptance rates across combinations are $M(AR_1)=81.7\%$, $M(AR_2)=96.4\%$, $M(AR_3)=98\%$, $M(AR_4)=92.1\%$. Hence, the most challenging objective is oLDD followed by oNS.

ii) It is possible to find four combinations of weights (i.e. c = 8, 9, 20, 26) that allow concurrently meeting the targets for oOR, oBED and oNS ($\hat{n}_2, \hat{n}_3, \hat{n}_4$, respectively) for all the 30 instances.

iii) The relationship between a W_i and AR_i is neither linear nor obvious. For example, AR_4=*100%*, can be obtained for W_4=0.990 (c=8), W_4=0.620 (c=9), W_4=0.495 (c=20), W_4=0.330 (c=24,28).

These simple observations suggest that it is meaningful to study the relationship between one weight (W_i) and the corresponding performance (AR_i) considering also the impact that the other weights exert on that same performance. To better understand the relationship between weights and acceptance rates, in the next section, we will perform a correlation analysis.

5.2.2 Correlation analysis and refinement of the weight space exploration

To investigate the relationship between weights and acceptance rates it is useful, at first, to look at the correlation coefficients $\rho_{i,k}$ between W_i and AR_k. Since our data violated the parametric assumptions, we used a non-parametric statistic, namely, the Spearman's rank correlation coefficient (Field et al. 2012, p.223). Such a coefficient allows assessing how well the relationship between two variables can be described using a monotonic function even if their relationship is not linear. The sign of the $\rho_{i,k}$ indicates the direction of association between W_i and AR_k. If AR_k tends to increase when W_i increases, $\rho_{i,k}$ correlation coefficient is positive and vice-versa. The magnitude of $\rho_{i,k}$ increases as W_i and AR_k become closer to being monotone functions of each other. The squared value of the Spearman coefficient $\rho_{i,k}{}^2$ represents the proportion of variance in the *ranks* that two variables share (Field et al. 2012, p.223). A large value of $\rho_{i,k}$, thus, implies that for those combinations for which W_i is larger than its median value, we can expect AR_k to be larger than its median value as well. Table 3 reports the coefficient $\rho_{i,k}$ and the associated p-values.

Table 3 Spearman's rank correlation coefficient ρ, 29 combinations of weights

$\rho_{i,k}$	AR_1	AR_2	AR_3	AR_4
W_1	0.67**	-0.56**	-0.48*	-0.38*
W_2	-0.55**	0.56**	0.04	-0.30
W_3	-0.03	-0.15	0.57**	-0.03
W_4	-0.21	0.15	0.01	0.78**
not significant $p > 0.05$, * $p < 0.05$, ** $p < 0.01$				

From Table 3 emerges a large positive correlation between W_i and AR_k for $i=k$, a large negative correlation between W_1 and AR_2 and between W_2 and AR_1, and a fairly large negative correlation between W_1 and AR_3, between W_1 and AR_4. All the other correlations are smaller and not statistically significant. In general, Table 3 suggests that since some weighs W_i are negatively correlated with the variable AR_k for $k \neq i$, they may affect the strength of the relationship between W_k and AR_k. In statistical terms W_i may act as *moderator* of the relationship between W_k and AR_k. To quantify the relationship between a given W_i (e.g. W_2) on a given AR_k (e.g. AR_1) while controlling the effects of the other weights (e.g. W_1, W_3, W_4) it is necessary to assess the semi-partial correlation between W_i and AR_k. In general, semi-partial correlation coefficients, allow explaining the variance in (the rank of) one particular variable (AR_k) from a set of predictor variables (W_1, W_2, W_3, W_4). Table 4 reports Spearman's semi-partial correlation coefficient $\rho s_{i,k}$.

Table 4 Spearman's rank semi-partial correlation coefficient ρs, 29 combinations of weights

$\rho s_{i,k}$	AR_1	AR_2	AR_3	AR_4
W_1	0.59**	-0.50**	-0.37	-0.41*
W_2	-0.57**	0.50**	0.09	-0.33
W_3	-0.10	-0.16	0.50**	0.01
W_4	-0.30	0.16	0.06	0.69**
not significant $p > 0.05$, * $p < 0.05$, ** $p < 0.01$				

Comparing Table 3 with Table 4, we observe that all the coefficients on the main diagonal of the correlation matrix are still significant, but smaller. It implies that the relationship between a weight W_i and the corresponding AR_i is *moderated* by the other weights. Interestingly $|\rho s_{2,1}|>|\rho_{2,1}|$ meaning that the correlation between W_2 and AR_1 increases (in absolute value) if we rule out the effects of the other weights on AR_1. Given the significant semi-partial correlation between W_1 and AR_2, between W_2 and AR_1 and between W_1 and AR_4 it is possible to state that:

- W_1 moderates the relationships between W_2 and AR_2, and between W_4 and AR_4;
- W_2 moderates the relationship between W_1 and AR_1.

Figure 1 displays, for example, the moderating effect of W_2 on the relationship between W_1 and AR_1. In the figure, AR_1 is plotted against W_1 using different tones of grey to identify the value of W_2 associated with each point. As can be noticed, if W_1 is higher than its median ($ME(W_1)$=0.25) also AR_1 tend to be higher than its median value ($ME(AR_1)$=0.73), in fact $\rho s_{1,1}$=0.59. In addition, for each value of W_1<0.5 low scores of AR_1 correspond to large values of W_2, in fact $\rho s_{2,1}$=-0.57. For each value of W_1>0.5 we have only one possible value of W_2, which is obviously smaller than 0.5.

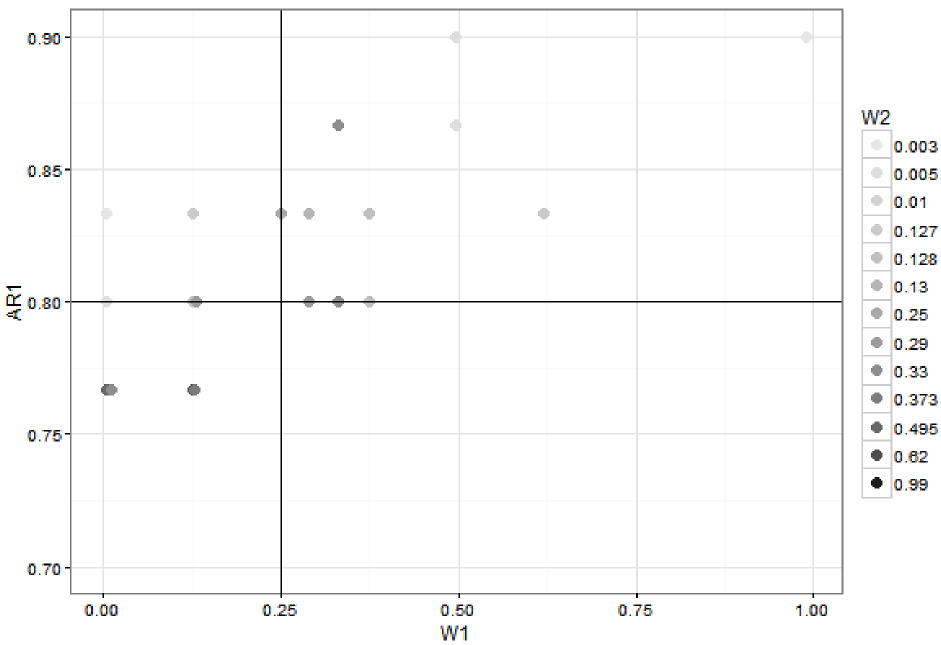

Figure 1 Moderating effect of W_2 on the relationship between W_1 and AR_1

These observations are useful to proceed in the exploration of the weight space. In fact, after the exploration of the first 29 combinations, we might be interested in exploring new weight combinations to identify solutions characterised by a large value of the most critical performance, i.e.

AR_1. This requires increasing the parameter defining the level of granularity to use in the weight space exploration, i.e. *maxLevel*. In our case, increasing *maxLevel* from 1 to 3, allows obtaining 56 new weight combinations (plus the 29 already explored).

Exploring additional 56 combinations, however, can be excessively time consuming. In this study, we argue that the Spearman's semi-partial rank correlation coefficients $\rho s_{i,k}$ can be used to select a meaningful subset of these new weight combinations. In fact, given the large positive value of $\rho s_{1,1}$(=0.59) and the large negative value of $\rho s_{2,1}$(=-0.57), it is reasonable to expand the exploration of the weight space to include only the combinations for which $W_1>ME(W_1)$ and $W_2<ME(W_2)$. Applying this heuristic selection criterion, indeed, reduces the number combinations to explore of more than one third (i.e. from 56 to 16). Table 5 shows, for each of value of AR_1 obtained in the exploration of the 56 additional weight combinations, the number C of combinations returning that value and the number of combinations that would have been excluded or included applying the mentioned selection criterion.

Table 5 Application of the selection criteria

AR_1	C	Excluded	Included
76.7%	4	4	0
80.0%	23	20	3
83.3%	27	16	11
86.7%	2	0	2
Tot	56	40	16

As can be noticed, the proposed selection criterion allows:

- exploring all the combinations leading to the highest value of AR_1;
- avoiding the exploration of all the combinations leading to the smallest value of AR_1;
- avoiding the exploration of 89% of the combinations leading to value of $AR_1 \leq ME(AR_1)=0.8$.

The (new) combinations of weights leading to the best results in terms of AR_1 are reported in Table 6.

Table 6 Newly added combinations of weights leading to the largest value of AR_1

c	W_1	W_2	W_3	W_4	AR_1	AR_2	AR_3	AR_4	d
30	0.435	0.188	0.188	0.188	86.7%	100.0%	100.0%	93.3%	*
31	0.805	0.065	0.065	0.065	86.7%	90.0%	96.7%	83.3%	30

Looking at Table 6, we can notice that the former combination (c=30) dominates the latter (c=31). In addition, combination 31 is not dominated by any of the 85(=29+56) combinations explored (due to space limitation the results of the 56 added combinations are not reported here). Unfortunately, none of the newly explored combinations returned values of AR_1 higher than those obtained in the first round of exploration.

Table 7 shows the values of ρs, calculated using all the 85 combinations of weights. As can be noticed, this expanded sample confirms the results coming from the first 29 observations: W_2 is negatively correlated with AR_1, W_1 is negatively correlated with AR_2, AR_3, AR_4, and each W_i is positively correlated with the corresponding AR_i.

Table 7 Spearman's rank semi-partial correlation coefficient ρs, 85 combinations of weights

$\rho s_{i,k}$	**AR_1**	**AR_2**	**AR_3**	**AR_4**
W_1	0.43**	-0.23*	-0.23*	-0.31**
W_2	-0.30**	0.34**	-0.01	-0.19
W_3	-0.04	-0.02	0.36**	0.00
W_4	-0.17	-0.04	-0.03	0.58**
not significant p > 0.05, * p < 0.05, ** p < 0.01				

6 Discussion

From the computational results it emerges that the model allows successfully meeting the challenging objectives of the Meyer Hospital's stakeholders. Across 30 instances, most of the weight combinations allows obtaining an *AR* of at least 80% for all the objectives. For oOR, oBED and oNS is even possible to concurrently obtain *AR*=100%. Nonetheless, the results reveal that for certain instances oLDD' target is difficult to meet and that very high values of *AR* for this objective (e.g. AR_1

=90%) are associated with a lower value of the other *ARs* (see for example c=2 and c=12 in Table 2). This is not surprising. To meet the targets relevant to oOR, oBED and oNS, the model can select surgery groups from a wide set of possible alternatives. Instead, to meet the oLDD target, the model is obliged to select surgery groups containing surgeries with approaching due-dates. Depending on the instance, this may imply selecting surgery groups with large ST and/or LoS. These type of surgery groups are more difficult to schedule, and consequently solutions can be characterised by unbalanced ORs and/or bed utilisations and/or an unsatisfying throughput. Obviously, the higher the weight associated with oLDD, the more such a phenomenon is amplified.

The trade-offs between objectives, obviously depend on the value chosen for the targets. Lowering the target would certainly allow obtaining *AR*=100% for all objectives. However, in situations were targets are challenging, is reasonable to assume that the target associated with oLDD is more complex to meet than the others. When this type of trade-off arises, the presented correlation analysis can help making sense of the unobvious relationship between the value of the weights and the performance obtained. This, in turn, can help performing a time-saving (additional) exploration of the weight space with the aim to find better solutions with respect to the critical objective. For example, the described trade-off between the *AR* relevant to oLDD and other *ARs* is well captured by the coefficients in Table 4 (and confirmed when the sample is expanded, see Table 7). These coefficients, in fact, demonstrate that when the weight assigned to oLDD (W_1) is above its median value and the one assigned to another objective k (W_k) is below its median value, then the acceptance rate AR_k tends to be lower than its median value as well. This type of insight can be used to refine the exploration of the weight space. In fact, if after a first exploration of the weight space one wants to find better solutions with respect to a generic performance P_i, it makes sense to (i) use the Jones & Tamiz (2010)'s algorithm to generate new and more fine-grained combinations of weights; (ii) calculate the $\rho s_{i,\mathrm{k}}$ matrix, and select the weights W_{k1} and W_{k2} that have, respectively, the largest positive and negative correlation with P_i; (iii) solve the goal programming model using only those weight combinations for which $W_{k1}>ME(W_{k1})$ and $W_{k2}<ME(W_{k2})$. Obviously as any heuristic approach the presented weight selection

criterion doesn't guarantee to explore the best possible combinations of weights. However, it certainly allows excluding a large number of weight combinations leading to poor solutions, while exploring only a limited set of "promising" combinations.

7 Conclusion and limitation

In this study, we presented a novel mixed integer goal-programming model which allows determining the *surgery groups* to be scheduled in a multiple day planning period (i.e. 2 weeks), in context where each specialty is pre-assigned to specific sessions, with the multiple objective of obtaining a *desired:* (i) patient due date fulfilment rate, (ii) OR utilisation, (iii) bed utilisation, (iv) number of scheduled surgeries. An extensive experimental campaign based on real data coming from a leading Italian hospital, revealed that the model in most of the cases allows meeting the targets fixed by the hospital' stakeholders. As expected, it also shows that it is not always possible to meet all the targets concurrently and suggests a way to perform an information-guided exploration of the weight space to find solutions representing a satisfactory trade-off. This study considers hospital features that are shared by a large number of the contributions available in the literature. Consequently, both the presented model and the following analysis can be of interest for a wide audience of practitioners and scholars.

This study has two main limitations. First, we investigated only one hospital setting. This led us to neglect hospital resources (e.g. ICU, electro-medical devices) or objectives that may be highly critical in other settings. Second, we have not investigated the scalability of the presented MIP model. As such we cannot predict how the model would behave if the planning horizon were extended or if the number of ORs and beds increases. These two issues clearly limit the external validity of our findings. Future research, thus, should be devoted at performing an extensive computational campaign including a large number of randomly generated and/or benchmark instances (i.e. those proposed by Leeftink & Hans 2016) and several combinations of target values.

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