Dominant strategies to reduce patient waiting time under multiple constrained resources

Nico Dellaert[1], **Jully Jeunet**[2]

1. *Technische Universiteit Eindhoven*
   School of Industrial Engineering
   Postbus 513
   5600MB Eindhoven
   The Netherlands
   N.P.Dellaert@tue.nl
2. *CNRS*
   Lamsade
   Université Paris Dauphine
   place du Maréchal de Lattre de Tassigny
   75775 Paris Cedex 16
   jully.jeunet@dauphine.fr

ABSTRACT. *Waiting times for elective procedures are a major health policy concern in many European countries. Initiatives to control waiting times involve supply-side policies that encompass raising public capacity, and demand-side policies with a prioritization of patients according to need for a better management of waiting lists. On a microeconomic level, complementary approaches to tackle the issue of waiting times include the use of Operational Research techniques. The present paper is in line with these approaches and provides strategies to reduce the waiting time for elective surgery in any speciality requiring multiple constrained resources. In the medium run, the objective is to determine the best admission policy at the tactical level. The resulting tactical plan which is based on a fixed number of patients derived from historical data of arrivals can be adjusted to patients in the queue to provide an operational plan. Several strategies to translate a tactical plan into an operational plan are considered and assessed in terms of hospital performance and patient satisfaction. We propose a new strategy that allows for substantial decrease in waiting time while keeping a high hospital performance. The hospital performance is measured by a weighted sum of several criteria such as additional and cancelled operations, plan changes and deviations of resource consumptions compared to their target levels. Weights in the hospital performance indicator are drawn at random in selected intervals to portray a wide spread of managers' assessments. Simulation results show that several strategies are dominant whatever the assessment profile. We also identify the best strategies to reach a limited waiting time.*

Journal européen des systèmes automatisés – n° 1/2016, 7-30

RÉSUMÉ. Les délais d'attente pour les chirurgies non urgentes constituent un enjeu majeur de santé publique dans la plupart des pays européens. Des initiatives de contrôle des temps d'attente s'appuient sur des politiques d'offre orientées vers une augmentation des capacités et des politiques axées sur la demande s'appuyant sur une priorisation des patients pour une meilleure gestion des listes d'attente. A un niveau microéconomique, des approches complémentaires incluent l'utilisation de techniques de recherche opérationnelle. Cet article exploite ce type de techniques pour développer des stratégies de réduction des délais d'attente des chirurgies électives, pour toute spécialité nécessitant le recours à de multiples ressources critiques.

A moyen terme, l'objectif est de déterminer la meilleure politique d'admission des patients au niveau tactique. Le plan tactique des chirurgies qui en résulte est établi sur la base d'un nombre fixe de patients déterminé à partir des historiques d'arrivée. Mais ce nombre diffère du nombre de patients qui seront effectivement enregistrés sur la liste d'attente. Le plan tactique peut alors être ajusté en fonction des patients de la liste afin de proposer un plan opérationnel des chirurgies. Nous considérons plusieurs stratégies d'adaptation du plan tactique à la liste d'attente afin d'obtenir un plan opérationnel des chirurgies et nous évaluons ces stratégies en termes de performance hospitalière et de satisfaction des patients. Nous définissons une nouvelle stratégie qui permet une réduction substantielle du temps d'attente tout en maintenant une performance hospitalière élevée. La performance hospitalière est mesurée par une somme pondérée de plusieurs critères comme les reports et les ajouts d'interventions chirurgicales, les changements du plan, les écarts entre consommation des ressources et leur valeur cible. Les pondérations dans cet indicateur de performance sont tirées au hasard dans des intervalles spécifiques de sorte à refléter un large éventail de profil d'évaluation par les gestionnaires d'hôpitaux. Les résultats des simulations montrent que plusieurs stratégies sont dominantes, quel que soit le profil d'évaluation. Nous identifions aussi les meilleures stratégies permettant d'atteindre un délai d'attente limité.

KEYWORDS: hospital performance, waiting time, assessment profile, dominance, tactical and operational planning, multiple constrained resources.

MOTS-CLÉS : performance hospitalière, délai d'attente, profil d'évaluation, dominance, planification tactique et opérationnelle, contraintes de ressources multiples.

DOI:10.3166/JESA.49.7-30

1. Introduction

Breakthroughs in surgical technology and new demographic trends (ageing population) entail rising costs of healthcare which is therefore a major concern for policy makers. With less tax money as a result of ageing population and the economic crisis, expenditure cuts are unavoidable and lead consequently to fewer available resources that affect waiting times. Most European countries have to deal with ever longer waiting times. The question is how to sustain health care systems with a satisfactory trade-off between patient satisfaction and resources use efficiency.

To improve hospital management performance, the use of Operational Research techniques has developed considerably over the years. Such techniques are increasingly and successfully used to model health care systems as discrete event simulation systems and to provide valuable planning and scheduling methods for elective and emergency patients. Organizational structure, strategic positioning or legal constraints make heterogeneity a characteristic feature of hospitals. This leads to a wide variety of modelling issues and development of proper solving methods. But, as in many other organizations, decision making in hospitals also occurs at two main levels. On the tactical level, (medium-term), the objective is to determine a master surgery plan that consists of a set of surgeries to be performed on each day of a medium run horizon including all relevant resources and their availability. On the operational level the problem is to schedule patients on a daily or weekly basis and usually considers more resources constraints that happen closer to the date of surgery. Obviously, the decision levels depend on each other since decisions made at one level provide input into the next decision level. Still, most papers take only one decision level into account (Cardoen *et al.* (2010)).

At the tactical level, several objectives with various granularities are examined. Blake and Donald (2002) or Beliën and Demeulemeester (2007) tackle the problem of allocating operating theatre resources to specialities. At a less aggregate level, other contributions consider the allocation of elective surgeries to operating room (OR) blocks (see van Oostrum *et al.* (2008); Adan and Vissers (2002) or Adan *et al.* (2009)). A large number of manuscripts take into account only one resource, the operating theatre, which is the bottleneck resource for most surgeries nowadays. First, a lot of surgeries are now performed on an outpatient basis. Second, the use of less invasive surgical techniques allow for a faster recovery which implies a limited consumption of other resources like beds and nursing care. However, for some types of surgery it is clearly not sufficient to consider only the operating theatre availability. For instance, cardiothoracic surgery procedures often require that patients spend several days in the Intensive Care Unit (ICU). For these surgeries, integrating downstream resources such as beds or nursing care in ICUs leads to a better overall performance (see McManus *et al.* (2003); Houdenhoven *et al.* (2007); Adan and Vissers (2002); Adan *et al.* (2009); Gupta (2007); Hulshof *et al.* (2013)). In a recent survey, Cardoen *et al.* (2010) recognize that although strides have been made, integration of hospital facilities such as ICU or Post-Anaesthesia Care Unit (PACU) still remain a major research issue.

At the operational level, the problem to be addressed is the so-called Surgical Case Assignment Problem (SCAP). Lamiri *et al.* (2008) develop an optimization model for OR planning with the objective of minimizing the expected OR overtime costs and the elective cases related costs, where the capacity needed for emergency is random. Houdenhoven *et al.* (2007) allow for flexibility in the use of OR blocks to schedule surgical cases with the goal of minimizing planned slack and the required number of OR blocks. Guinet and Chaabane (2003) determine an operating theatre solution satisfying capacity constraints related to several critical resources while minimizing the overload and patient waiting time costs for each day spent in the hospital before surgery. Lin *et al.* (2013) develop a multi-objective simulation optimisation framework to determine optimal resource levels in surgical services.

A few contributions examine several decision levels simultaneously. Testi *et al.* (2007) propose a three-phase approach for scheduling surgery rooms, including the strategic decision level. Other papers derive an operational schedule from a tactical plan, using an open scheduling strategy (see for instance Guinet and Chaabane (2003) or Jebali *et al.* (2006)). Testi and Tanfani (2009) develop an integer programming model to solve concurrently the master surgery planning problem and the surgical case assignment problem with the aim of minimizing patient welfare loss related to excess waiting. Only OR resources are taken into account and the major contribution is to directly consider the patient perspective by including prioritization in the objective function. Ma and Demeulemeester (2013) propose a three-stage integrative approach to the planning problem under bed and OR block capacity, including the case mix planning phase, the master surgery scheduling phase and the operational performance evaluation phase.

Most of the strategies to reduce waiting time are based on prioritization. Comas *et al.* (2008) use a simulation model to show that a prioritization system for cataract surgery decreases waiting time compared with the First In First Out system. Patrick *et al.* (2008) formulate the problem of scheduling patients with different priorities to a diagnostic facility as a Markov decision process. These two contributions deal with outpatient procedures and consider consequently a single resource contrary to Hulshof *et al.* (2013) who integrate prioritization in a tactical planning problem with multiple resources. Persson and Persson (2009) suggest an approach combining simulation and optimisation to model surgery decisions for patients with different priorities and using several resources.

The present paper considers the elective surgery planning problem under multiple constrained resources in a two-stage approach based on Adan *et al.* (2011). At the tactical level (first stage), we use the mixed integer programming formulation that Adan *et al.* (2009) developed to solve the case mix planning problem for elective cardiac surgery. The resulting tactical plan which is based on a fixed number of patients derived from historical data of arrivals can be adjusted to patients in the queue at the operational level (second stage), using the flexibility rule proposed by Adan *et al.* (2011). The authors also suggest a slack planning rule that, like the flexibility rule, allows for substantial decrease in waiting time.

In addition to the two-above mentioned rules, we propose in this paper to update the tactical plan according to the waiting list. This research is thus one of the few to deal with more than one decision level, multiple constrained resources and to offer strategies specifically dedicated to shorten waiting times. Combining the three rules (flexibility, slack planning and updating) leads to different operational plans for which several performance indicators can be computed. Unlike most papers that only consider OR utilization and costs as measures of the hospital performance at the operational level (see Guerriero and Guido (2011)) we propose a compound indicator, namely the global deviation indicator, to reflect the hospital performance. This indicator is a weighted sum of several criteria such as additional or cancelled operations, plan changes and deviations of resources consumptions compared to their target levels. In practice it is very hard for hospital managers to provide an objective assessment of weights to the various criteria. Based upon interviews we define reasonable intervals for each weight. We test the efficiency of our strategies for a large number of randomly selected weights. Thus we can determine the relative dominancy of each strategy. For this test we use a simulation model based on a case study from a Dutch thoracic surgery centre.

Therefore, the contribution of this paper is twofold. First we provide an additional strategy to reduce waiting time, the updating strategy. Second, analyzing thoroughly this strategy as well as those of Adan *et al.* (2011), we show that some of them are always dominant, whatever the weights assigned to the components of the hospital performance indicator. Thus, for any speciality requiring multiple constrained resources, we offer several valuable strategies to get efficient operational plans in terms of patient satisfaction and hospital performance, with a trade-off between these two dimensions. Hence, the final choice of a particular strategy will depend on the strategic positioning of the hospital.

The next section provides the mathematical model for the tactical planning problem and the parameters values are displayed in Annex A. Section 3 describes the rules to get improved operational plans from tactical plans and summarizes the approach. Section 4 presents the performance criteria from the patient and the hospital perspectives that we used to assess the strategies. Section 5 is dedicated to the experimental framework. Simulation results are commented in Section 6. Section 7 draws the main conclusions of the paper.

2. The tactical planning problem

In the medium run, the problem is to determine a tactical plan for elective patients with the aim of allocating at best limited resources while operating on all patients that are expected during a typical horizon. Adan *et al.* (2009) formulate this problem as a Mixed Integer Program (MIP) where the objective is to minimize the sum of deviations between expected resources consumption and their target levels of utilization. Four resources are considered: the operating theatre hours (OT), the number of beds in the ICU (IC), the number of beds in the Medium Care Unit (MC) and the nursing hours in the ICU (NH). The formulation of the tactical planning problem is based on the functioning of the Thorax Centre Rotterdam, where patients were grouped in $N = 8$ categories, each of these categories being relatively homogenous in terms of consumption of ICU and operating room resources. Table 1 provides for each patient category examples of surgical procedures performed and the expected number of hours to operate on one patient in each group (s_c). We then give the number of pre-operative days for each category (l_c), the average number of patients (λ_c) over a 4-week horizon and the target throughput of patients (V_c) to be operated on within this horizon. For any category c, the average number of patients is based on historical data for arrivals and the target throughput of patients V_c is obtained by rounding up the average number of patients. For instance, patients in category 3 undergo a coronary bypass, with an operation duration $s_3 = 4$ hours, and are admitted in the MCU $l_3 = 1$ day before surgery. There is an average of $\lambda_3 = 66.02$ patients in this category that are operated on over a 28-day horizon, thus the target throughput of patients in this category is set to $V_3 = 67$ patients.

Table 1. Patient groups, OT hours, pre-operative days, average number of patients and target throughputs

Patient group (c), N=8	**Example of procedures**	**OT hours (s_c)**	**Pre-op. day (l_c)**	**Average # patients (λ_c)**	**Target throughput (V_c)**
(1) Child, simple	Closure ventricular septal defect	4	0	7.36	8
(2) Child, complex	Arterial switch	8	0	9.36	10
(3) Adult, short OT, short IC	Coronary bypass (CABG)	4	1	66.02	67
(4) Adult, long OT, short IC	Mitral valve plasty	8	1	12.73	13
(5) Adult, short OT, middle IC	CABG with expected medium IC	4	1	2.64	3
(6) Adult, long OT, middle IC	Heart transplant	8	1	1.55	2
(7) Adult, long OT, long IC	Thoraco-abnominal aneurysm	8	1	0.36	1
(8) Adult, very short OT, no IC	Cervical mediastinoscopy	2	1	6.91	7

Formally, the objective is to determine the values of variables $\{x_{c,t}\}$, representing the number of patients in category c planned for surgery on day t, $\forall c = 1, \ldots, N$ and $\forall t = 1, \ldots, T$, for which the daily expected utilization of each resource deviates as little as possible from the daily target utilization level which is set by the hospital management usually between seventy and eighty percent of the maximum capacity. To formulate the problem we adopt the notation and definitions in Table 2.

The objective function to be minimized can be written as

$$\sum_{r \in \{\text{OT,IC,NH,MC}\}} \alpha_r \sum_{t=1}^{T} (o_{r,t} + u_{r,t}) \,. \tag{1}$$

The relative weight α_r for resource r used in the objective function is defined as

$$\alpha_r = \frac{g_r / \sum_{j=1}^{T} A_{r,j}}{\sum_{r=\{\text{OT,IC,MC,NH}\}} \left(g_r / \sum_{j=1}^{T} A_{r,j} \right)}, \tag{2}$$

with values of target utilization levels $\{A_{r,j}\}$ that are displayed in Annex A (Table 5) and g_r denotes the importance of resource r as assessed by the stakeholders in the hospital. We have $g_{\text{OT}} = 8, g_{\text{IC}} = 10, g_{\text{MC}} = 3, g_{\text{NH}} = 5$. These weights reflect the degree of flexibility of each resource. Thus, g_{IC} was set to a greater value than that of g_{OT} because finding an extra bed in the ICU was considered as more difficult than calling for an additional surgeon (for a detailed discussion, see Adan *et al.* (2011)).

Table 2. Notation

Parameters	
N	Number of patient categories.
c	Category index, $c = 1, \ldots, N$.
T	Length of the cyclic planning horizon, in days.
t	Day index, $t = 1, \ldots, T$.
V_c	Target number of elective patients in category c to be operated on during the horizon.
s_c	Surgery duration in hours for a patient in category c.
l_c	Number of pre-operative days in the MCU for a patient in cat. c.
r	Resource index, $r \in \{\text{OT,IC,NH,MC}\}$.
$L_{\text{ICU}}^{\max}$	Maximum length of stay recorded in the ICU over all patient categories.
$L_{\text{MCU}}^{\max}$	Maximum length of stay recorded in the MCU over all patient categories.
$p_{\text{ICU},c,j}$	Probability that a patient in category c is in the ICU, j days after surgery, $j = 0, 1, 2, \ldots, L_{\text{ICU}}^{\max}$.
$p_{\text{MCU},c,j}$	Probability that a patient in category c is in the MCU, j days after surgery, $j = 0, 1, 2, \ldots, L_{\text{MCU}}^{\max}$.
$w_{c,j}$	Intensive care nursing workload (in hours) required for a patient in category c, j days after surgery.
$K_{r,t}$	Maximum capacity for resource r on day t (expressed in number of hours for OT and NH and in number of beds for IC and MC).
$A_{r,t}$	Target level of utilization of resource r on day t.
α_r	Relative importance of resource r as assessed by the stakeholders of the hospital.

Variables	
$x_{c,t}$	Number of patients in category c planned for surgery on day t, with $c = 1, \ldots, N$ and $t = 1, \ldots, T$.
$o_{r,t}$	Over utilization of resource r on day t, relative to its target level of utilisation, with $r \in \{\text{OT,IC,NH,MC}\}$ and $t = 1, \ldots, T$.
$u_{r,t}$	Under utilisation of resource r on day t, relative to its target level of utilisation, with $r \in \{\text{OT,IC,NH,MC}\}$ and $t = 1, \ldots, T$.

The total number of patients in group c to be operated on over the T-day cycle must be equal to the target patient throughput V_c. Hence

$$\sum_{t=1}^{T} x_{c,t} = V_c, \quad c = 1, \ldots, N. \tag{3}$$

The expected utilization of the OT by the patients must satisfy

$$\sum_{c=1}^{N} s_c \cdot x_{c,t} \leq K_{\text{OT},t}, \;\; t = 1, \ldots, T. \tag{4}$$

and

$$-u_{\text{OT},t} \leq \sum_{c=1}^{N} s_c \cdot x_{c,t} - A_{\text{OT},t} \leq o_{\text{OT},t}, \;\; t = 1, \ldots, T. \tag{5}$$

The expected number of utilized beds in the ICU must satisfy the following inequalities

$$\sum_{c=1}^{N} \sum_{j=0}^{L_{\text{ICU}}^{\text{max}}} p_{\text{ICU},c,j} \cdot x_{c,t-j} \leq K_{\text{IC},t}, \;\; t = 1, \ldots, T. \tag{6}$$

and

$$-u_{\text{IC},t} \leq \sum_{c=1}^{N} \sum_{j=0}^{L_{\text{ICU}}^{\text{max}}} p_{\text{ICU},c,j} \cdot x_{c,t-j} - A_{\text{IC},t} \leq o_{\text{IC},t}, \;\; t = 1, \ldots, T. \tag{7}$$

In the above constraints we used the convention that the subscript $t - j$ in $x_{c,t-j}$ should be treated modulo T: day 0 is the same as day T, day -1 is the same as day $T - 1$ and so on.

For the expected number of utilized nursing hours in the ICU, we must have

$$\sum_{c=1}^{N} \sum_{j=0}^{L_{\text{ICU}}^{\text{max}}} w_{c,j} \cdot p_{\text{ICU},c,j} \cdot x_{c,t-j} \leq K_{\text{NH},t}, \;\; t = 1, \ldots, T. \tag{8}$$

and

$$-u_{\text{IC},t} \leq \sum_{c=1}^{N} \sum_{j=0}^{L_{\text{ICU}}^{\text{max}}} w_{c,j} \cdot p_{\text{ICU},c,j} \cdot x_{c,t-j} - A_{\text{IC},t} \leq o_{\text{IC},t}, \;\; t = 1, \ldots, T. \tag{9}$$

Similarly, the expected number of utilized beds in the MCU must satisfy

$$\sum_{c=1}^{N} \sum_{j=1}^{l_c} x_{c,t+j} + \sum_{c=1}^{N} \sum_{j=0}^{L_{\text{MCU}}^{\text{max}}} p_{\text{MCU},c,j} \cdot x_{c,t-j} \leq K_{\text{MC},t}, \;\; t = 1, \ldots, T. \tag{10}$$

and

$$-u_{\mathrm{MC},t} \leq \sum_{c=1}^{N}\sum_{j=1}^{l_c} x_{c,t+j} + \sum_{c=1}^{N}\sum_{j=0}^{L_{\mathrm{MCU}}^{\max}} p_{\mathrm{MCU},c,j} \cdot x_{c,t-j} - A_{\mathrm{MC},t} \leq o_{\mathrm{MC},t}, \quad t = 1, \dots, T. \tag{11}$$

As operating rooms on weekends are dedicated only to emergency patients, we have to require that

$$x_{c,t} = 0 \text{ and } x_{c,t+1} = 0, \quad t = 6 + 7(j-1); \quad j = 1, \dots, (T/7); \quad c = 1, \dots, N. \tag{12}$$

Our tactical planning problem therefore consists in minimizing the objective function in (1) subject to constraints (3) to (12) with the following integrality constraints

$$x_{c,t} \in \{0, 1, 2, \dots\}, \quad c = 1, \dots, N; \quad t = 1, \dots, T. \tag{13}$$

The decision variables consist of the number of patients in each category planned for surgery on each day, the over and under utilization of each resource compared to its target level of utilization on each day. All parameters values are given in Annex A. This MIP can be solved using branch-and-bound approaches with CPLEX.

3. From tactical plans to improved operational plans

Our aim is to translate the tactical plan resulting from the optimization program described in Section 2 into an operational plan. At the operational level, the number of patients in the queue of each group may deviate too much from the average which is used to compute the tactical plan. Therefore, the tactical plan must be adjusted to get a feasible operational plan. This adjustment can be performed with different levels of flexibility, depending on the hospital managers' preference for an operational plan that sticks more or less closely to the tactical plan. The adjustment strategy presented here is called flexibility strategy. Section 3.1 describes this strategy and the way it is used to obtain an operational plan. Section 3.2 presents two strategies to get improved operational plans. First, the slack planning strategy consists in increasing the target throughput of patients on the basis of which the tactical plan is calculated. More capacity is thus reserved at the tactical level leading to additional slots that can be used at the operational level for a better management of the waiting list. Second, a new strategy is proposed in this paper, the updating strategy that amounts to compute a new tactical plan regularly on the basis of updated target throughput values according to the waiting list of patients.

3.1. Flexibility strategy to get an operational plan

Let us recall that $x_{c,t}$ designates the number of patients in category c planned for surgery on day t at the tactical level. Values of $x_{c,t}$ are solutions to the MIP described in Section 2. We let $y_{c,t}$ be its equivalent definition in the operational plan. The number of elective patients in category c actually arriving on day t is denoted by $D_{c,t}$. Patient arrival is assumed to follow a Poisson process, with $D_{c,t} \rightsquigarrow P(\lambda_c/T)$, where λ_c is the average number of patients over a $T-$day horizon. Furthermore, we let $Q_{c,t}$ be the number of patients in category c in the queue on day t, with

$$\begin{array}{l} Q_{c,1} = Q_{c,0} + D_{c,1}, \\ Q_{c,t} = Q_{c,t-1} - y_{c,t-1} + D_{c,t}, \ \ \forall t > 1, \end{array} \tag{14}$$

where $Q_{c,0}$ is the initial waiting list which is usually already populated. On each day and for each category, the flexibility strategy is used to compare $Q_{c,t}$ to $x_{c,t}$ so as to determine $y_{c,t}$. Once all categories have been considered, we obtain an operational plan for day t. On the next day, new elective patients arrive and the waiting list is updated following Eq. (14). The flexibility strategy is applied again and so on. After T days, we get an operational plan for one cycle. The flexibility strategy involves three options: no flexibility, medium and full flexibility that we also used in Adan *et al.* (2011).

No flexibility. We follow the tactical plan unless the number of patients in the waiting list is less than the planned number, in which case some planned operations are cancelled. Formally, we have $y_{c,t} = \min(x_{c,t}, Q_{c,t})$.

Full flexibility. When we apply the full flexibility option, the only information we use from the tactical plan is the total number of operation slots for that day (i.e. $\sum_{c=1..N} x_{c,t}$), and we fill these slots with patients having the longest waiting times. This means that some planned categories are finally not scheduled in the operational plan and replaced with unplanned ones.

Medium flexibility. In the operational plan, the slots are first filled with planned patients at the tactical level. If the number of planned patients is greater than the number of patients in the waiting list, there are unfilled slots that we fill with the longest waiting time patients from other planned categories. Unplanned categories are not considered, so ultimately some slots could be empty. Note that with this alternative, a group that is not in the tactical plan but in the waiting list is never scheduled for surgery in the operational plan.

3.2. Improvement strategies

The two improvement strategies we consider both lead to alternative tactical plans and therefore to different operational plans.

3.2.1. Slack planning

The slack planning rule which we already used in Adan *et al.* (2011) creates additional slots at the tactical level by increasing the target throughput of patients. This allows for a better management of the waiting list, with no impact on the capacity utilisation at the operational level because patient arrivals remain unchanged. Two options are included: no slack and large slack.

No slack. In the Thorax Centre problem, the no slack planning option amounts to calculate the tactical plan on the basis of unmodified target throughput $V = \{8, 10, 67, 13, 3, 2, 1, 7\}$ (see Table 1, last column).

Large slack. The number of patients per group is calculated in such a way that less than 5% of patients have to wait more than one cycle. In the Thorax Centre problem, the large slack planning option leads to the stream of target throughputs $V = \{9, 11, 70, 15, 4, 3, 2, 9\}$.

3.2.2. Updating

In this paper we propose an additional improvement rule, the updating rule, that consists in computing a new tactical plan regularly on the basis of updated values of target throughput of patients according to the waiting list. It is reasonable to assume that the planning horizon actually involves several T-day cycles for which an operational plan is computed, starting off with an initial tactical plan using either the no slack planning option or the large slack planning one. To update the tactical plan, we compute for each category new values of target throughput by replacing part of the mean, λ_c, with a fraction of the initial waiting list, Q_c^{init} which corresponds to the list at the end of the previous cycle. Actually one week of patients $(1/4)\lambda_c$ is replaced with half of the waiting list $(1/2)Q_c$. Thus, if the initial waiting list contains two weeks of patients, target throughput values remain unchanged; they are however increased if the waiting list involves more than two weeks of patients and decreased should the opposite occur. Commonly to the approaches in control theory, to avoid oscillation, this difference is only partly implemented with factor 1/3. Letting $[x]$ denote the nearest integer to x, updated values of target throughput for each category, V_c^u, are therefore computed according to

$$V_c^u = \left[V_c + (1/3)\left((1/2)Q_c^{init} - (1/4)\lambda_c\right)\right], \ \forall c = 1, \dots, N, \qquad (15)$$

where V_c denotes the initial value of the target throughput of patients in category c. The values we chose for the parameters in Eq. (15) lead to reasonable updated target throughput values, with a moderate sensitivity to the variations of the waiting list. Other values could have been explored but with the chosen ones, we already obtained a good performance of the updating rule (see Section 6). Simulation results also show that most often, the differences between yearly and quarterly updates are tenuous, meaning that updating or not matters more than the updated values of target throughputs themselves. We consider three options for updating the tactical plan: **no update, yearly and quarterly updates.**

3.3. Summary of the approach

Figure 1 summarizes the approach where the rules are represented by red circles. At the tactical level (left hand side of the figure), the slack planning rule is applied so as to get two different sets of values for the target throughput of patients in each category V_c. The data of the hospital (values for parameters defined in Table 2 and provided in Annex A) are used to formulate the MIP problem which is solved using the commercial optimization software package CPLEX. The tactical plan is the solution to the problem. At the operational level (right hand side), the waiting list is updated daily with actual arrivals of patients following Eq. (14). Based on the waiting list, the updating rule can be applied to get a new tactical plan, if the current day corresponds to an updating period (for instance day 365 or 730 for a yearly update). The flexibility rule is then used to adjust the tactical plan to the waiting list. An operational plan is obtained in this way.

In the following, we use the term ‘strategy’ to designate a combination of the three rules’ options. Combining the two options for the slack planning, the three options for flexibility and the three updating periodicities results into eighteen strategies to get an operational plan or equivalently to eighteen different operational plans.

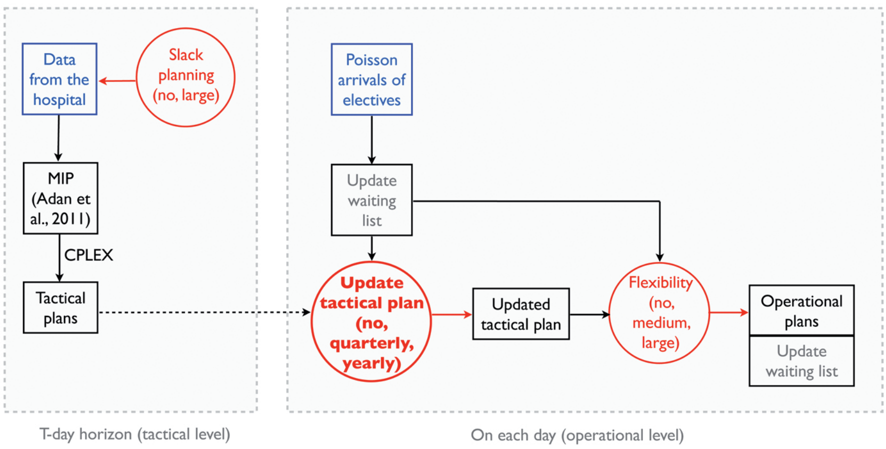

Figure 1. Methodology to get tactical and operational plans

4. Performance criteria

Every operational plan is assessed in terms of patient satisfaction and hospital performance. It should be noted that evaluating the quality of an operational plan amounts to assessing the strategy which was used to get the plan.

4.1. Patient satisfaction

The average waiting time is chosen as a measure of patient satisfaction. The waiting time of any patient is defined as the period between her/his arrival day in the waiting list and the day on which the surgery is scheduled in the operational plan. The average waiting time per cycle is defined as the ratio of the sum of all patient waiting times to the total number of arrivals during the cycle.

4.2. Hospital performance

The hospital performance is measured through a compound index of the following deviation indicators.

Total number of cancelled operations (TC). This indicator counts the total number of planned slots at the tactical level that are unused at the operational level. Unused slots can be seen as cancelled operations since some reserved capacities are finally unconsumed. We let $I_{\{a\}}$ be a binary variable that takes the value of one if condition a is met and zero otherwise. Indicator TC is given by

$$TC = \sum_{c=1}^{N} \sum_{t=1}^{T} (x_{c,t} - y_{c,t}) \cdot I_{\{x_{c,t} > y_{c,t}\}}. \tag{16}$$

Additional operations from planned categories (AO). For patient categories planned for surgery on each day of the tactical plan, we count the number of extra slots that are used in the operational plan compared to those in the tactical plan. Extra slots, namely additional operations, imply that surgeons and equipment are still mobilised but for more work. We let $I_{\{a;b\}}$ be a binary variable that takes the value of one if conditions a and b are met simultaneously and zero otherwise. Indicator AO is written as

$$AO = \sum_{c=1}^{N} \sum_{t=1}^{T} (y_{c,t} - x_{c,t}) \cdot I_{\{x_{c,t} > 0; y_{c,t} > x_{c,t}\}}. \tag{17}$$

Additional operations from unplanned categories (AC). This indicator provides the number of operations in the operational plan from categories that were not initially planned at the tactical level. We have

$$AC = \sum_{c=1}^{N} \sum_{t=1}^{T} y_{c,t} \cdot I_{\{x_{c,t} = 0\}}. \tag{18}$$

Thus, if in the tactical plan no operation of category c was planned on day t and if some patients of that category are finally scheduled on that day, we must mobilise the corresponding specialised surgeons and associated resources.

Plan changes (PC). This indicator measures the differences between two tactical plans if we use the updating rule, by summing the number of new categories that are planned over a cycle. Plan changes are to be penalised because doctors allocate surgery days to their agenda and these days then need to be modified. As we are in the medium run, we do not know precisely what will finally be the number of operations in the operational plan, so it is better to reason in terms of working days in surgeons' agendas, rather than in terms of number of patients to be operated on during these working days. Formally, the indicator of plan changes is given by

$$PC = \sum_{c=1}^{N} \sum_{t=1}^{T} x_{c,t}^{u} \cdot I_{\{x_{c,t}=0\}}, \tag{19}$$

where superscript u refers to the use of the updating rule.

Target deviations. We consider the target deviations, TD_r, for all resources $r \in$ {OT,IC,NH,MC} at the operational level, with $TD_r = \sum_{t=1}^{T}(u_{r,t} + o_{r,t})$, where under utilisation $u_{r,t}$ and over utilisation $o_{r,t}$ on day t express the differences between resources consumptions and target utilisation levels determined at the operational level. These targets are no longer defined as a percentage of the available capacities as they were at the tactical level but on the basis of average actual consumption of each resource over the week.Average consumptions were computed from pilot simulation runs where operational plans were obtained with no slack planning, no flexibility and no updating. The consumption of resources associated with an operational plan is calculated in a similar fashion to expected consumptions at the tactical level variables $x_{c,t}$ are replaced with $y_{c,t}$, for all resources and all periods. To compute the consumption of beds in the ICU and in the Medium Care Unit (MCU) and the nursing hours in the ICU, we used the actual lengths of stay of each patient, rather than the expected lengths of stay we considered in the tactical plan.

The hospital performance is measured through a global deviation indicator, GD, which is a weighted sum of the five previous deviation indicators:

$$GD = \omega_{TC}TC + \omega_{AO}AO + \omega_{AC}AC + \omega_{PC}PC + \omega_{TD} \sum_{r \in \{\text{OT,IC,NH,MC}\}} \alpha_r TD_r. \tag{20}$$

To each manager corresponds a combination $(\omega_{TC}, \omega_{AO}, \omega_{AC}, \omega_{PC}, \omega_{TD})$ of weights and thus a particular assessment of the hospital performance, for given values of the five deviation indicators. As these indicators values are different for each strategy, we thus have a global deviation indicator value for each manager and for each strategy. For a manager, a strategy is dominant (or efficient) if there is no other strategy allowing for a better waiting time with a no worse hospital performance (and conversely). Values assigned to the weights ω will be discussed in Subsection 5.2. Weights $\{\alpha_r\}_{r\in\{\text{OT,IC,NH,MC}\}}$ in Eq. (20) reflect the flexibility level of each resource as assessed by the stakeholders in the hospital relative to their average consumption at the operational level. These weights should therefore be distinguished from the other weights in Eq. (20) because they are fairly less judgemental.

Table 3 provides an illustration of the way the four deviation indicators are calculated, based on a simple example with 2 categories of patients over a 3-day cycle. Indicators AO, AC and TC result from a comparison between $x_{c,t}$ and $y_{c,t}$. For instance, each time the number of patients in the tactical plan is greater than this number in the operational plan, TC cumulates the differences. Indicator PC compares the initial tactical plan to the updated one. In the example, there is only one new category planned over the cycle (category 1 on day 3).

Table 3. A simple example of deviation indicators

	$c = 1$			$c = 2$			Sum
Day t	1	2	3	1	2	3	
Tactical $x_{c,t}$	**5**	**3**	**0**	**1**	**2**	**2**	
Operational $y_{c,t}$	**3**	**2**	**1**	**1**	**0**	**4**	
TC	2	1	0	0	2	0	**5**
AO	0	0	0	0	0	2	**2**
AC	0	0	1	0	0	0	**1**
Updated tact. $x^u_{c,t}$	**4**	**3**	**2**	**0**	**2**	**3**	
PC	0	0	1	0	0	0	**1**

5. Experimental framework

The rationale for using simulations to assess the performance of our strategies relies on the very limited possibilities to analyse them exactly.

5.1. Simulation model

Using CPLEX 12.1, we first computed an initial tactical plan under each slack planning option (no slack or large slack). At the beginning of every cycle, depending upon the chosen updating periodicity (no update, yearly or quarterly update) if the tactical plan had to be revised, updated values of target throughputs for each category were computed using Eq. (15) and CPLEX was called to obtain a new tactical plan. Then on each day of the cycle, patient arrivals were simulated according to a Poisson process. The waiting list was updated by adding the arrivals (see Eq. (14)). For each category, patients in the waiting list were compared to the planned slots at the tactical level using one of the three flexibility rule options (no flexibility, full or medium). Some patients were thus removed from the waiting list to be assigned to the operational plan. Next, the consumption of the resources was computed based on actual lengths of stay in the ICU and in the MCU that were drawn according to the empirical distributions obtained from the hospital. At the end of every cycle and after the warm-up period, the waiting time and the deviation indicators described in Section 4.2 were computed and recorded for each of the eighteen strategies.

5.2. Parameters setting

The number of new elective patients on each day was assumed to follow a Poisson process with parameter λ_c/T, with $T = 28$ and values λ_c displayed in Table 1. A warm-up period of 80 cycles was required to reach the steady state. For each of the 18 strategies, we performed 5 replications of patient arrivals and lengths of stay over 180 cycles (including the warm-up period) that led to a total number of 2340 calls to CPLEX 12.1 to get the tactical plans. We thus decided to run CPLEX for a fixed CPU time of 5 minutes. Furthermore, running CPLEX twice as long did not bring any significant improvement of gaps to optimality. We recorded 500 values (5 replications of 100 cycles) of the waiting time and deviation indicators that we averaged to obtain mean values for each strategy.

As explained in Section 4.2, on the operational level, target levels of utilisation for the resources are based on their average consumption associated with operational plans. From pilot runs consisting of several draws of patients' arrivals that are confronted with the tactical plan (under no slack planning) to get operational plans with no flexibility, we computed the resulting average consumptions of resources and, using definition in Eq. (2), we obtained in this way $\alpha_{\text{OT}} = 0.152$, $\alpha_{\text{IC}} = 0.773$, $\alpha_{\text{MC}} = 0.044$, $\alpha_{\text{NH}} = 0.031$. Values of the other weights in Eq. (20) represent managers' assessment of the degree of disruption in the organisation caused by each source of deviation. For instance, total cancellations and additional operations can be considered either equally or unequally troublesome. Based on interviews with managers from several hospitals, we formulate the following assumptions.

– Additional operations (AO) are at least as troublesome as cancelled operations (TC) as it is harder to mobilise more surgeons and equipment than using less resources than planned. We have $\omega_{AO} \geq \omega_{TC}$ and ω_{AO} is at most equal to 10 times ω_{TC}.

– Additional operations for unplanned categories (AC) are at least as disordering than additional operations from planned categories (AO) because AC require the organisation of a new surgery session, which implies for instance surgeons to come to the hospital although not initially planned. We thus have $\omega_{AC} \geq \omega_{AO}$ and we assume that ω_{AC} should not exceed twice the value of ω_{AO}.

– Adding a new session in the tactical plan is at least as disrupting as adding new operations from unplanned categories in the operational plan: $\omega_{PC} \geq \omega_{AC}$. The larger the updating periodicity is, the higher the number of plan changes is, so we assume that ω_{PC} is at most equal to η times ω_{AC} where η, the updating periodicity, takes the value of 3 and 10 for the quarterly and the yearly update, respectively.

– As target deviations TD represent the kernel of the tactical plan, they are assigned the highest weights.

Weights in Eq. (21) reflect these assumptions. We set $\omega_{TC} = 1$ throughout and we consider uniformly discrete distributed values for the other weights over large but relevant plausible intervals:

$$\begin{cases} \omega_{AO} \rightsquigarrow U\left[1, 10\right], \\ \omega_{AC} \rightsquigarrow U\left[\omega_{AO}, 20\right], \\ \omega_{PC} \rightsquigarrow U\left[\omega_{AC}, \eta\omega_{AC}\right], \\ \omega_{TD} \rightsquigarrow U\left[\omega_{AC}, 40\right]. \end{cases} \tag{21}$$

Preliminary runs showed that a number of 5'000 draws of weights values was large enough since the moments for ω_{AO} were very close to their expected values. We thus obtained 5'000 evaluations of the hospital performance for each strategy.

To summarize the simulation approach, we first recorded 500 values (5 replications of 100 cycles) of the waiting time and deviation indicators that we averaged for each of the 18 strategies. Thus, to each strategy corresponds a single average value of the waiting time, and a single average value for each indicator TC, AO, AC, PC, TD. Then for each manager assessment or equivalently for each of the 5'000 combinations of weights ω, and for each strategy, we compute the global deviation indicator according to (20). Thus, each strategy has a 2 dimensional evaluation for each manager.

6. Simulation results

Table 4 displays for each strategy the average waiting time and the average increase of the global deviation indicator compared to minimum over the weights for which the examined strategy is dominant. The minimum value of the global deviation indicator is always provided by the no slack, no flexibility and no update strategy (strategy #16 in Table 4) over the 5'000 combinations of weights, each of them representing an assessment profile of the hospital performance. The last column provides the frequency at which the strategy is dominant, or alternatively the percentage of managers who consider the strategy as a dominant one.

Some strategies are (nearly) always dominant whereas others never are. These strategies are such that the assessment profile has no influence on their dominance. Strategies that are always dominated (strategies 9 to 12) combine opposite options for slack planning and flexibility: it is never efficient to use full flexibility with no slack planning or large slack planning with no flexibility and yearly update. All other combinations of these two rules are (nearly) always dominant if updating is not implemented (strategies 1, 4, 7, 13 and 16). Conversely, all strategies with a dominance frequency much lower than 100% make use of the updating rule. Although all weights play a part, we noticed that updating is dominant only for specially low values of weights associated with plan changes (ω_{PCY} and ω_{PCQ}).

Table 4. Performance of the strategies

Strategy				Av. waiting	Av. deviation	Dominance
#	Slack	Flex.	Update	time (days)	increase (%)	freq. (%)
1	Large	Full	No (N)	1.13	118.91	100.00
2			Quart. (Q)	1.82	102.91	77.72
3			Year (Y)	1.91	103.27	50.42
4		Med.	N	2.47	68.55	98.68
5			Q	3.56	54.67	52.66
6			Y	3.53	56.14	83.12
7		No	N	5.84	27.46	100.00
8			Q	7.66	25.98	5.50
9			Y	8.70	–	**0.00**
10	No	Full	N	4.21	–	**0.00**
11			Q	7.16	–	**0.00**
12			Y	9.02	–	**0.00**
13		Med.	N	8.15	16.89	99.66
14			Q	9.46	13.21	14.58
15			Y	9.61	15.42	4.26
16		No	N	26.81	0.00	100.00
17			Q	13.89	12.38	44.42
18			Y	14.70	11.59	34.24

Figure 2 plots each strategy as a circle with a diameter proportional to its dominance frequency. Whatever the assessment profiles, there exists a trade-off between patient satisfaction and hospital performance as the best waiting times are obtained at the price of high global deviation indicator values, and conversely. It appears that slack planning leads to a clear reduction in the average waiting time because the number of slots is increased whereas patient arrivals remain the same. This allows for a better management of the waiting list. However, slack planning is detrimental to the target deviations for all resources because increasing the number of slots offers more opportunities to over utilise resources in some periods whereas target utilisation levels remain unchanged: values of over utilisation for each resource increase a lot from the no slack situation to the slack one. The deviation indicators are roughly higher under the large slack planning option, since additional slots potentially generate more possibilities of cancelling and adding unplanned patients.

The average waiting time clearly improves with more flexibility. It reaches its minimum value under the full flexibility option since priority is given to the categories with the highest waiting times. Introducing more flexibility has however a negative impact on target deviations. The lowest target deviation values are obtained under the no flexibility option as we stick as closely as possible to the tactical plan that seeks to minimise the deviations. An increasing flexibility is obviously associated with higher values of indicators: TC, AO, AC.

When used solely, the updating strategy contributes to a significant decrease of the average waiting time while improving target deviations for all resources and two of the schedule instability indicators, namely TC and AO but indicator PC obviously degrades.

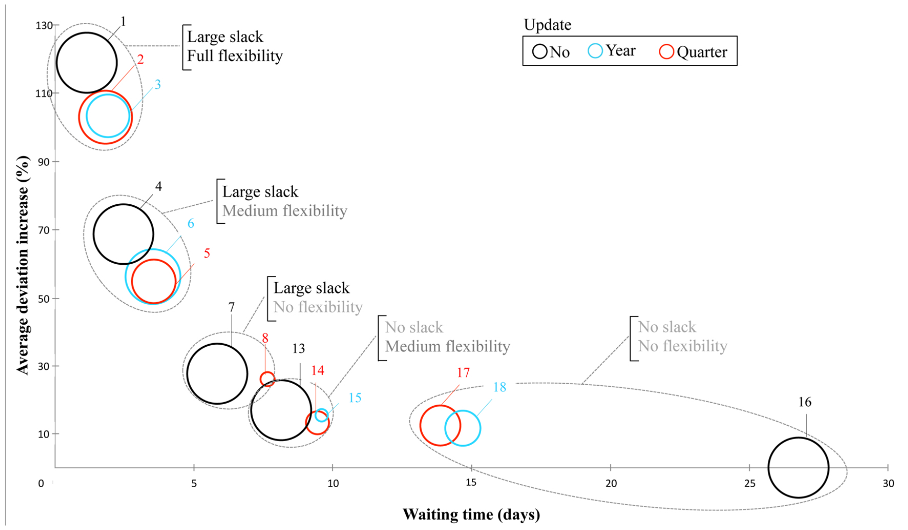

Figure 2. Strategies with non-zero dominance frequencies

For a hospital manager, choosing amongst his/her dominant strategies depends on the hospital strategic positioning.

Focusing essentially on hospital performance. In a competitive environment where hospitals seek for cost control and profit increase that can be invested in new activities or technologies, profit maximisers would be willing to choose strategies that bring the minimum global deviation indicator values. Of these, the no slack, no flexibility and no update strategy (strategy 16) maximises the hospital performance, but the corresponding waiting time is the largest one and hospitals may fear a loss of patients who would go to hospitals or clinics with a shorter waiting time. Thus, if hospital managers are not reluctant to plan changes (low values of weights ω_{PCY} and ω_{PCQ}), the single use of the updating strategy offers a tremendous waiting time reduction of about 50% at the expense of a slight increase (of about 12%) in the global deviation indicator value (strategies 17 and 18).

Seeking for low waiting times. Low waiting time values, from about 1 day to less than 4 days, are reached using the large slack planning option combined with either full flexibility (lowest waiting times) or medium flexibility and these strategies are always Pareto dominant as long as updating is not performed (strategies 1 and 4). If managers assign low weights to plan changes, updating can be Pareto dominant and leads to an improvement of the hospital performance because target deviations are decreased. Hospital managers may choose one of these strategies if their concern is to reach a high patient satisfaction at the expense of a low hospital performance, and if the medical staff is willing to accept short-term modifications of their agendas (indicators TC, AO, AC are increased).

Reaching a compromise between hospital performance and waiting times. We consider intermediate waiting time values to be in the range 5-10 days. Such values can be obtained by using either large slack planning or medium flexibility. Updating in this case rarely leads to Pareto dominance. For these intermediate waiting times, if hospital managers are more concerned with patients' satisfaction, they can choose to use solely the large slack planning option (strategy 7). If they want to increase the hospital performance at the expense of a waiting time increase, they can select the medium flexibility strategy (strategy 13), provided that the medical staff is relatively flexible about short-term timetable changes.

7. Conclusion and future research

Applying the method developed by Adan *et al.* (2009), we obtained a tactical plan that we adjusted to the number of patients in the queue using a flexibility rule with different priority levels based upon the waiting time (Adan *et al.* (2011)). In this way we obtained feasible operational plans. To get improvements in terms of waiting time, we also used the slack planning rule and proposed here a new rule: updating the tactical plan. Combining the options of the three rules: flexibility, slack planning and updating led to eighteen strategies that were assessed through two main indicators: the waiting time reflecting patient satisfaction and a global deviation indicator as a measure of the hospital management performance. The global deviation indicator is a weighted sum of several indicators with weights drawn at random in selected intervals to portray a wide spread of managers' assessments. Based upon data from a Dutch thoracic surgery centre, simulations showed that some strategies are (nearly) always dominant whereas others never are. Low waiting time values (about 1 to 4 days) are reached when both slack planning and flexibility (either full or medium) are used. Intermediate waiting times (5 to 10 days) are obtained by using either slack planning or medium flexibility. If the focus is on the hospital performance, the single use of updating offers good solutions with the lowest average global deviation increases of about 12% compared to the minimum and a waiting time which is almost reduced by 50 %. This shows how important is the impact of the tactical plan on the waiting time. Our results show that long waiting lists go along with hospital performance and in many countries waiting lists are kept long to have efficient resources use in hospitals. However the current policy in the Netherlands is to keep waiting lists really short.

The advantage of our strategies is that they can be applied to many specialities requiring multiple constrained resources. They are currently implemented in a large French hospital, in an orthopaedic department dealing with numerous elective surgeries (e.g. musculoskeletal cancers) for which care pathways imply time and space constraints related not only to the availability of operating rooms, staff and beds inside the department but also to radiation and chemotherapy sessions outside of the department at later stages in the treatment process. Future work is to provide refinements of the strategies to get additional waiting time values to choose from. Another research plan is to develop heuristic solution approaches to the Mixed Integer Program for the tactical planning problem.

References

Adan I., Bekkers J., Dellaert N., Jeunet J., Vissers J. (2011). Improving operational effectiveness of tactical master plans for emergency and elective patients under stochastic demand and capacitated resources. *European Journal of Operational Research*, Vol. 213, pp. 290-308.

Adan I., Bekkers J., Dellaert N., Vissers J., Yu X. (2009). Patient mix optimization and stochastic resource requirements: A case study in cardiothoracic surgery planning. *Health Care Management Science*, Vol. 12, pp. 129-141.

Adan I., Vissers J. (2002). Patient mix optimisation in hospital admission planning: a case study. *International Journal of Operations and Production Management*, Vol. 22, pp. 445-461.

Beliën J., Demeulemeester E. (2007). Building cyclic master surgery schedules with levelled resulting bed occupancy. *European Journal of Operational Research*, Vol. 176, pp. 1185–1204.

Blake J., Donald J. (2002). Mount sinaï hospital uses integer programming to allocate operating room time. *Interfaces*, Vol. 32, pp. 63-73.

Cardoen B., Demeulemeester E., Beliën J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research*, Vol. 201, pp. 921-932.

Comas M., Castells X., Hoffmeister L., Roman R., Cots F., Mar J. *et al*. (2008). Discrete-event simulation applied to analysis of waiting lists. evaluation of a prioritization system for cataract surgery. *Value in Health*, Vol. 7, pp. 1203-1213.

Guerriero F., Guido R. (2011). Operational research in the management of the operating theatre: a survey. *Health Care Management Science*, Vol. 14, pp. 89-114.

Guinet A., Chaabane S. (2003). Operating theatre planning. *International Journal of Production Economics*, Vol. 85, pp. 69-81.

Gupta D. (2007). Surgical suites' operations management. *Production and Operations Management*, Vol. 16, pp. 689-700.

Houdenhoven M. V., Oostrum J. V., Hans E., Wullink G., Kazemier G. (2007). Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical case scheduling. *Anesthesia and Analgesia*, Vol. 105, pp. 707-714.

Hulshof J., Boucherie R., Hans E., Hurink J. (2013). Tactical resource allocation and elective patient admission planning in care processes. *Health Care Management Science*, No. 16, pp. 152-166.

Jebali A., Alouane A. H., Ladet P. (2006). Operating room scheduling. *International Journal of Productions Economics*, Vol. 99, pp. 52-62.

Lamiri M., Xie X., Dolgui A., Grimaud F. (2008). A stochastic model for operating room planning with elective and emergency demand for surgery. *European Journal of Operational Research*, Vol. 185, pp. 1026-1037.

Lin R., Sir M., Pasupathy K. (2013). Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: specific application to determining optimal resource levels in surgical services. *Omega*, No. 41, pp. 881-892.

Ma G., Demeulemeester E. (2013). A multilevel integrative approach to hospital case mix and capacity planning. *Computers and Operations Research*, Vol. 40, pp. 2198-2207.

McManus M., Long M., Cooper A., Mandell J., Berwick D., Pagano M. (2003). Variability in surgical caseload and access to intensive care services. *Anesthesiology*, Vol. 98, pp. 1491–1496.

Oostrum J. V., Vanhoudenhoven M., Hurink J., Hans E., Wullink G., Kazemier G. (2008). A master surgery scheduling approach for cyclic scheduling in operating room departments. *OR Spectrum*, Vol. 30, pp. 355-374.

Patrick J., Puterman M., Queyranne M. (2008). Dynamic multipriority patient scheduling for a diagnostic resource. *Operations Research*, Vol. 6, pp. 1507-1525.

Persson M., Persson J. (2009). Health economic modelling to support surgery management at a swedish hospital. *Omega*, No. 37, pp. 853-863.

Testi A., Tanfani E. (2009). Tactical and operational decisions for operating room planning: Efficiency and welfare implications. *Health Care Management Science*, Vol. 12, pp. 363-373.

Testi A., Tanfani E., Torre G. (2007). A three-phase approach for operating theatre schedules. *Health Care Management Science*, Vol. 10, pp. 163–172.

Annex A. Data of the hospital

The data are based on the Thorax Centre Rotterdam, used in Adan *et al.* (2011). Patients have been grouped in $N = 8$ categories, each of these being relatively homogeneous in terms of the resources consumption. For each of the resources, r, there exists a maximum available capacity per day t, $K_{r,t}$ and a target utilization level $A_{r,t}$ usually set between 70% and 80% of the capacity. These values are displayed in Table 5 and apply to every week in the 4-week planning cycle ($T = 28$). With these values of $A_{r,t}$ and $g = \{8, 10, 3, 5\}$ we are able to compute the relative weights α in the objective function, using Eq. (2).

Four operating theaters are available nine hours a day during the week days. The Intensive Care Unit (ICU) has 10 available beds throughout the working week and 8 beds during the week end. The Medium Care Unit (MCU) has 36 beds available every day. The available ICU nursing staff is matched with the number of beds in the ICU, except on the week ends on which the staff is reduced.

The nursing hours in the ICU $\{w_{c,t}\}$ required per day for patients in categories 1 to 7 are estimated to 12 hours throughout their stay in the ICU unless for the second day spent in the ICU for categories 5, 6 and for the second and third day for category

Table 5. Capacity and target utilization levels for the resources

	OT hours		**IC beds**		**MC beds**		**IC nursing hours**	
	Capacity	Target	Capacity	Target	Capacity	Target	Capacity	Target
Day (t)	($K_{\mathrm{OT},t}$)	($A_{\mathrm{OT},t}$)	($K_{\mathrm{IC},t}$)	($A_{\mathrm{IC},t}$)	($K_{\mathrm{MC},t}$)	($A_{\mathrm{MC},t}$)	($K_{\mathrm{NH},t}$)	($A_{\mathrm{NH},t}$)
Monday	36	29	10	7	36	27	133	91
Tuesday	36	29	10	7	36	27	133	91
Wednesday	36	29	10	7	36	27	133	91
Thursday	36	29	10	7	36	27	133	91
Friday	36	25	10	7	36	27	133	91
Saturday	0	0	8	2	36	27	52	26
Sunday	0	0	8	2	36	27	52	26

7 for which the needs are 24 hours. Patients in category 8 require only 3 hours of ICU nursing per day whatever their length of stay in the ICU. The longest stay in the ICU equals 10 days ($L_{\mathrm{ICU}}^{\max} = 9$).

We use a stochastic length of stay in the ICU and in the MCU, based on empirical data. Table 6 provides the probability $p_{\mathrm{ICU},c,j}$ that a patient in category c is in the ICU j days after surgery, $j = 0, \ldots, L_{\mathrm{ICU}}^{\max}$, with $L_{\mathrm{ICU}}^{\max} = 9$. For instance, any patient in category 8 has 21% of chance to be in the ICU zero days after surgery, that is the day of surgery ($p_{\mathrm{ICU},8,0} = 0.21$) . In such a case, the patient will only stay overnight in the ICU.

Table 6. Probabilities $p_{ICU,c,j}$, for all $c = 1, \ldots, 8$ and for all $j = 0, \ldots, L_{ICU}^{max}$

	Day									
Patient group (c), N=8	0	1	2	3	4	5	6	7	8	9
(1) Child, simple	0.93	0.07	0.05	0.02	0	0	0	0	0	0
(2) Child, complex	1	0.09	0.02	0	0	0	0	0	0	0
(3) Adult, short OT, short IC	0.99	0.16	0.05	0.02	0.01	0.01	0.01	0	0	0
(4) Adult, long OT, short IC	1	0.19	0.09	0.04	0.04	0.03	0.01	0.01	0.01	0.01
(5) Adult, short OT, middle IC	1	0.2	0.13	0.07	0.07	0.07	0.07	0	0	0
(6) Adult, long OT, middle IC	1	1	0.86	0.43	0.29	0.14	0.14	0.14	0	0
(7) Adult, long OT, long IC	1	1	1	1	1	1	1	0	0	0
(8) Adult, very short OT, no IC	0.21	0	0	0	0	0	0	0	0	0

Table 7 provides the same information type for the MCU. For instance, $p_{\mathrm{MCU},6,23} = 0.29$ means that any patient in category 6 has 29% chance to be in the MCU 23 days after surgery. We have $L_{\mathrm{MCU}}^{\max} = 27$.

The target number of patients V_c in each category to be operated on during the 4-week horizon is based on historical data of arrivals, their values are displayed in Table 1.

Table 7. Probabilities $p_{MCU,c,j}$, for all $c = 1, \ldots, 8$ and for all $j = 0, \ldots, L_{MCU}^{max}$

	Day													
Patient group (c), N=8	0	1	2	3	4	5	6	7	8	9	10	11	12	13
(1) Child, simple	0.05	0.26	0.26	0.26	0.26	0.21	0.14	0.07	0	0	0	0	0	0
(2) Child, complex	0	0.13	0.17	0.17	0.17	0.17	0.17	0.13	0.09	0.08	0.06	0.06	0.06	0.06
(3) Adult, short OT, short IC	0.01	0.84	0.94	0.97	0.95	0.66	0.42	0.29	0.21	0.15	0.11	0.09	0.07	0.05
(4) Adult, long OT, short IC	0	0.78	0.88	0.93	0.93	0.84	0.68	0.53	0.35	0.25	0.22	0.19	0.18	0.13
(5) Adult, short OT, middle IC	0	0.8	0.87	0.93	0.93	0.87	0.8	0.6	0.6	0.4	0.33	0.33	0.13	0.07
(6) Adult, long OT, middle IC	0	0	0.14	0.57	0.71	0.86	0.86	0.86	1	1	0.86	0.86	0.86	0.86
(7) Adult, long OT, long IC	0	0	0	0	0	0	0	1	1	1	1	1	1	1
(8) Adult, very short OT, no IC	0.64	0.54	0.41	0.26	0.13	0.1	0.08	0.08	0.03	0.03	0	0	0	0

Continued	Day													
Patient group (c), N=8	14	15	16	17	18	19	20	21	22	23	24	25	26	27
(1) Child, simple	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(2) Child, complex	0.06	0.04	0.02	0.02	0.02	0	0	0	0	0	0	0	0	0
(3) Adult, short OT, short IC	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0	0	0	0	0	0	0
(4) Adult, long OT, short IC	0.1	0.06	0.06	0.06	0.04	0.04	0.04	0.03	0.03	0.01	0.01	0.01	0.01	0.01
(5) Adult, short OT, middle IC	0.07	0.07	0	0	0	0	0	0	0	0	0	0	0	0
(6) Adult, long OT, middle IC	0.71	0.71	0.71	0.71	0.57	0.57	0.57	0.43	0.43	0.29	0.14	0	0	0
(7) Adult, long OT, long IC	1	1	1	0	0	0	0	0	0	0	0	0	0	0
(8) Adult, very short OT, no IC	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Article soumis le 4/09/2014
Accepté le 17/09/2015