Reallocate operating room time among surgical services

The case of a public Portuguese hospital

Maria Luísa Metello Coutinho de Carvalho Lubomirska

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Instituto Superior Técnico

Abstract - Health care providers are facing a continuous increase in the complexity of their organizations mainly due to the increasing demand and to the development of new and expensive technologies. The operating room (OR) is a major challenge in the hospital and is important for the financial health of the hospital. Moreover, it has a large impact in several units of the hospital and on the workforce of the immediate downstream units. In the last decades, surgery demand has been increasing, forcing operating rooms to be more efficiently and effectively managed. This work is developed under a partnership with a Portuguese public hospital and aims to contribute to a major social impact, which is the reduction of patients on the waiting list Given the hospital restrictions in terms of space and human resources, this work focus on the reallocation of the operating room time among the surgical services, proposing a new master surgical schedule – a timetable with the number of slots, day and room in which each specialty should operate. This reallocation has as main objective to match demand and the existing capacity while maximizing the OR efficiency. This work proposes a mixed integer linear programming, with four distinct objectives; to maximize the allocated slots and aggregated preferences, to match supply and demand and to level the workload of up- and downstream units. A comparison of the actual allocation of slots with the one suggested by this approach is performed. Results show that the workforce is one of the major restrictions, suggesting a new distribution of the workforce among the specialties.

Keywords - Operating Room; Master Surgical Schedule; Capacity Planning; Waiting Time; Mixed Integer Linear Programming

I. Introduction

Health care providers are facing a continuous increase in the complexity of their organizations. This complexity can be related with the evolution of two main variables: the increasing demand and the development of technologies in the health sector. Within the services provided by hospitals, surgical activity is a major center of costs and revenues. Surgical suites (SS) represent more than 40% of hospitals costs and profits and are considered by some authors as the engine of the organization (Beliën & Demeulemeester, 2007; Blake & Donald, 2002). Surgery involves high specialized medical staff and equipment which have high costs associated. Among the variables of complexity mentioned before, this activity includes a high level of variability and uncertainty related to demand, stakeholders and material availability. Surgical activities have not only an intrinsic high complexity but also a large social responsibility. To guarantee quality of health care, surgical activities should be held in a certain time frame. This time corresponds to the days, months or even years in a waiting list for surgery. A greater service level is achieved with a lower number of days that a patient waits to the procedure. This work aims to develop a model to optimize the use of the available SS resource while matching surgical supply and demand, and therefore to reduce the waiting list of surgical procedures. The next sections will present a literature review, in Section II, the model formulation, in Section III, the application of the model in a real case study, Section IV and some final conclusions in Section V.

II. Literature Review

Health care systems can be characterized by its complexity and by the enormous pressure to cut costs (Brandeau et al. 2004). The need for efficiency, due to financial pressures, and the complexity within health care organizations makes them, hospitals in particular, an important and rich area for the development and use of OR/MS tools and frameworks. Management of health care operations deals with problems that concern the operations which include planning and manage of the various facilities. The problems can go from a high-level of decision as the design of health care supply chain or design of facilities, to decisions of medium term as capacity planning, process selection or equipment evaluation and selection. It can also include problems of short-term decisions such as capacity management, scheduling and workforce planning, inventory management and management of system performance and quality (Brandeau et al. 2004). This work focusses on the capacity planning problem of the SS, included in the medium-term or tactical decisions.

The SS is one of the services, in a hospital facility, that consumes more resources. This consumption can be related with the large amount of specialized medical equipment (e.g. anesthetic machine, OR table, lighting general and special) and with the required specialized medical staff composed of surgeons, nurses and anesthesiologists. To deal with these costs, it is important to use the resources in an effective and efficient way, leading to its maximum utilization and reduced waste. Thus, the SS requires planning to analyze points of inefficiency and management towards optimization. The literature on capacity planning of the SS can be classified by the different levels of decisions or by the different characteristics of the problem in terms of types of patients and other facilities than the SS. Furthermore, the management of the SS time can follow three different strategies: block scheduling, open scheduling, and modified block scheduling. Open scheduling allows surgeons to use any of the time slots (OR, day and period) according to their needs. This approach allows more flexibility, which means that it follows the dynamic of the evolution of the waiting lists, and it can also increase the efficient utilization of the ORs (Agnetis et al., 2012). Liu et al. (2011), based on the model created by Fei et al. (2010), develop a heuristic approach to solve an operating room scheduling problem with open scheduling strategy. This heuristic has as objective to maximize the operating room's efficiency and minimize the overtime cost. This is based on the idea that no time slot is reserved for a particular surgeon, and therefore, surgeons can use all available time slots and compete for OR time. Their results are positive, especially in the cases where the SS has large dimensions, enabling the algorithm to find always feasible and good quality solutions. Modified block scheduling tries to achieve the benefits of both previous strategies: stability and flexibility. According to Yahia et al. (2014), there are few authors mentioning the application of this approach. This work focusses on the block scheduling approach.

Inside the block scheduling approach, many variants of the problem can be found in the literature, either in the way the problem is solved or by the different objectives that another author proposes to answer. Therefore, the tendency, considering a certain period, is either the achievement of better results or the increase of problems complexity. Blake & Donald (2002) focus on the equitable distribution of time blocks among the SGs while Agnetis et al. (2012) takes another step and assigns block times to SGs with the possibility to dynamically adapt the number of hours allocated to each SG according to the current state of the waiting list. Regarding also only the SS, Day et al. (2012) differs from the previous papers since it combines open access scheduling and dedicated slots, and minimizes underutilized OR time and overtime. In 2007, articles gained a new dimension when Beliën & Demeulemeester (2007) and Santibáñez et al. (2007) added down-stream units to the SS capacity planning problem. This inclusion is justified by the large consequences that the SS has on many other units within the hospital. Zhang et al. (2009) distinguish from other papers as being the only to study the impact that the SS has on upstream units. The main objective is to minimize inpatients' length of stay (LoS) in the wards waiting for the surgery when constructing a weekly MSS. Recently Guido & Conforti (2017) use a multi-objective integer linear programming model to consider trade-offs among underutilization of OR capacity, balanced distribution of OR time among SGs, minimization of surgeries' waiting times and overtime working hours.

This work covers the gap in the literature, integrating some of these important issues. The assembled objectives are the allocation of the slots according to the overall waiting list, as Malik et al. (2015), the distribution of slots according to the preferences of the stakeholders (surgeons), as Penn et al. (2017), and including restrictions of up- and downstream units in terms of capacity and human resources as Dellaert & Jeunet (2017).

This work proposes a mathematical model which assembles objectives already seen by other authors but never studied together.

III. Model Formulation

This section presents the model formulation. In subsection 1 the case under study is introduced, including its characteristics and challenges, followed by the strategy to overcome those challenges. In subsection 2 the mixed-integer programming (MILP) formulation is presented.

1) Problem Statement

The case under study is a public Portuguese hospital located in Évora, in the region of Alentejo Central. This hospital has a central SS is composed of 5 operating rooms (ORs) and a post-anesthesia care unit (PACU). These ORs serve 8 surgical specialties which consist of general surgery, urology, orthopedics, ophthalmology, plastic surgery, pediatric surgery, otorhinolaryngology (ORL) and stomatology. To organize the SS each OR is reserved for one or more specialties: ORs 1 and 2 are usually for general surgery, urology, stomatology, pediatric surgery and plastic surgery; OR 3 is reserved for urgencies and for ORL interventions; OR 4 is reserved for orthopedic interventions; and OR 5 is reserved to ophthalmology, due to its small dimensions. The primary objective of this work is to turn the SS more effective and efficient by reallocating the operating room time among the surgical services. In order to plan the SS activities, the hospital uses a block scheduling strategy as is the case of most of the public hospitals in Portugal. In the block scheduling strategy, time slots (i.e., a combination of an OR, a day and a period) are assigned to a specialty or to a surgeon group (Samudra et al., 2016). This is the strategy of an MSS and this approach is used by several authors in several contexts (e.g. Beliën & Demeulemeester, 2007; Blake et al., 2002; Santibáñez et al. 2007) for providing a higher stability to managers and to the medical staff. This stability affects managers by giving a more predictable pattern of bed occupancy, in the pre- and post-operative room, required staff and required material (Agnetis et al., 2012). To propose a new and better MSS, implies to understand which characteristics of the SS must be considered, implying the recognition of the case study problems aligned with the characteristics covered by the literature. This SS is a unit that lives from the daily adaptation of the stakeholders, to reach their patients' needs and to cover the hospital shortages. Therefore, in order to build a new and better MSS it is required knowledge of the current difficulties and challenges that the SS faces. Important insights were given by the SS manager, surgeons, anesthesiologists and nurses. These interviews have greatly assisted this study in understanding the objectives and the constraints which the model should tackle, resulting in four main points: Maximization of the number of allocated slots, restricted by the availability of surgeons and anesthesiologists; Balance between supply and demand, restricted by the stability needed from a month to another; Balance of the utilization of the up- and downstream units; maximization of stakeholder's satisfaction.

2) MILP Formulation

Notation for the standard MILP is first introduced, including sets, subsets, parameters and decision variables. Then, the weighted-sum objective function is presented and finally the constraints.

- Sets

- $d \in D$: days from Monday (d=1) to Friday (d=5)

- $w_m \in W_m$: Weeks of each month m

- $m \in M$: Months

- $r \in R$: Operating rooms

- $b \in B$: Shifts

- $s \in S$: Specialties

- $i \in I$: Surgeons

- $a \in A$: Anesthesiologists

- $z \in Z = \{Q, I, W\}$: Set of resources (Q= pre-ward; I=ICU; W=ward)

- $n \in \{1, \ldots, N\_s\hat{}Q\}$: Days of a patient of specialty s in the pre-ward

- $n \in \{1, \ldots, N\_s\hat{}I\}$: Days of a patient of specialty s in the ICU after surgery

- $n \in \{1, \ldots, N\_s\hat{}OW\}$: Days of a patient of specialty s in a ward after surgery

- $n \in \{1, \ldots, N\_s\hat{}IW\}$: Days of a patient of specialty s in a ward after ICU

- $h \in H$: Wards

- $s \in S\_h$: Set of specialties accommodated by ward

- $l_m \in L_m = \{1, \ldots, |W_m| * 7\}$: Days in the MSS cycle-days within the month m

- Parameters

- $slots_m$: $total\ number\ of\ slots\ on\ month\ m$: $slots_m = |R| \times |B| \times |D| \times |W_m|$

- asd_s: $average\ surgery\ duration\ for\ specialty\ s$

- λ_s: $average\ number\ of\ operated\ patients\ per\ slot\ (mwdbr)\ and\ specialty$

- P_{sm}: $number\ of\ patients\ of\ specialty\ s\ waiting\ for\ surgery\ on\ the\ first\ day\ of\ each\ month\ m$

- t_{sm}: $target\ allocation\ for\ each\ specialty\ s\ per\ month$

- d_{sd}: $number\ of\ available\ surgeons\ from\ specialty\ s\ \ on\ day\ d$

- da_d: $number\ of\ available\ anesthesiologists\ on\ day\ d$

- k_{isdb}: $preference\ score\ specified\ by\ surgeon\ i\ of\ specialty\ s\ for\ day\ d\ on\ shift\ b$

- k_{adb}: $preference\ score\ specified\ by\ anesthesiologist\ a\ for\ day\ d\ on\ shift\ b$

- a_{ismwdb}: $\begin{cases} 1, if\ surgeon\ i\ of\ specialty\ s\ is\ available\ on\ month\ m, week\ w, on\ day\ d\ shift\ b \\ 0,\ otherwise \end{cases}$

- a_{amwdb}: $\begin{cases} 1, if\ anesthesiologist\ a\ is\ available\ on\ month\ m, week\ w, on\ day\ d\ shift\ b \\ 0,\ otherwise \end{cases}$
- ww_i: *number of times that a surgeon i of specialty s can go to the OR in a week*
- ww_a: *number of times that an anesthesiologist a can go to the OR in a week*
- Δ_w: $weekly\ stability$
- Δ_m: $monthly\ stability$
- $\alpha_{1,2,3}$: $weighted\ parameters\ for\ the\ three\ objectives$: $to\ adjust\ the\ model\ to\ the\ values\ of\ different\ hospitals, or\ for\ the\ user\ to\ explore\ the\ various\ objectives$
- g_s: $probability\ that\ a\ patient\ of\ specialty\ s\ is\ admitted\ in\ the\ ICU\ immediately\ after\ surgery$
- $c_s^z(n)$: $probability\ that\ a\ patient\ from\ surgery\ of\ specialty\ s\ stays\ n \in \{1, \dots, N_s^z\}\ days\ in\ resource\ z$
- d_{sn}^z: $probability\ of\ a\ patient\ of\ specialty\ s\ in\ the\ ICU\ to\ be\ discharged\ from\ the\ resource\ on\ day\ n$
- e_{sn}^Q: $probability\ that\ a\ patient\ of\ specialty\ s\ is\ in\ pre-ward\ on\ day\ n$
- e_{sn}^I: $probability\ that\ a\ patient\ of\ specialty\ s\ who\ had\ surgery\ on\ day\ 1\ is\ in\ the\ ICU\ on\ day\ n$
- e_{sn}^{OW}: $probability\ that\ a\ patient\ of\ specialty\ s\ who\ had\ surgery\ on\ day\ 1\ is\ in\ a\ ward\ on\ day\ n$
- e_{sn}^{IW}: $probability\ that\ a\ patient\ of\ specialty\ s\ who\ had\ surgery\ on\ day\ 1\ is\ in\ a\ ward\ on\ day\ n\ after\ staying\ m\ days\ in\ the\ ICU$
- e_{sn}^W: $probability\ that\ a\ patient\ of\ specialty\ s\ who\ had\ surgery\ on\ day\ 1\ is\ in\ a\ ward\ on\ day\ n$
- F_{sl}^z: $distribution\ on\ the\ lth\ day\ of\ a\ cycle\ of\ the\ number\ of\ recovering\ patients\ of\ specialty\ s\ in\ the\ resource\ z$
- $\bar{F}_s^z$: $distribution\ of\ the\ number\ of\ recovering\ patients\ in\ resource\ z\ on\ day\ l\ of\ the\ MSS\ cycle$
- w_z:$relative\ weight\ of\ resource\ z$
- u_z: $a\ nonnegative\ number\ such\ that\ the\ normalized\ weights\ w_z\ sum\ up\ 1$
- C_{zl}: *available capacity of resource z on day l*
- U_{zl}: *target utilization of resource z on day l*

- <u>Decision Variables</u>

- x_{smwdbr}: $\begin{cases} 1, if\ specialty\ s\ is\ assigned\ on\ month\ m, week\ w, on\ day\ d, to\ block\ b, OR\ r \\ 0, otherwise \end{cases}$

$$\forall\ s \in S, m \in M, w \in W_m, d \in D, b \in B, r \in R$$

- t_{sm}^-: $number\ of\ slots\ allocated\ to\ specialty\ s\ below\ its\ target\ on\ month\ m$
- t_{sm}^+: $number\ of\ slots\ allocated\ to\ specialty\ s\ above\ its\ target\ on\ month\ m$
- UU_{zl}: $under-utilization\ of\ resource\ z\ on\ day\ \ell \quad \forall\ z \in \{Q, I, W\},\ l \in L$
- OU_{zl}: $over-utilization\ of\ resource\ z\ on\ day\ \ell \quad \forall\ z \in \{Q, I, W\},\ l \in L$

- <u>Auxiliary Variables</u>

- y_{smwdbr}: $\begin{cases} 0, if\ the\ specialty\ s\ remains\ on\ the\ same\ slot\ (m, w, d, b, r)\ from\ week\ 1\ to\ week\ w \\ 1,\ otherwise \end{cases}$

$$\forall\ s \in S, m \in M, w \in W_m, d \in D, b \in B, r \in R\ \ l \in L$$

- j_{smwdbr}: $\begin{cases} 0, if\ the\ specialty\ s\ remains\ on\ the\ same\ slot\ (m, w, d, b, r)\ from\ month\ 1\ to\ month\ m \\ 1,\ otherwise \end{cases}$

$$\forall\ s \in S, m \in M, w \in W_m, d \in D, b \in B, r \in R$$

- w_{sm}: $\begin{cases} 0,\ if\ t_{sm}^-\ is\ greater\ than\ zero \\ 1,\ if\ t_{sm}^+\ is\ greater\ than\ zero \end{cases} \quad \forall\ s \in S, m \in M$

- Objective Function

Maximize:

$$\alpha_1 \sum_{s\in S}\sum_{w\in W}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R}\left(\frac{\sum_{i\in I} k_{isdb}}{|i|}+\frac{\sum_{a\in A} k_{adb}}{|a|}\right)x_{smwdbr} - \alpha_2 \sum_{s\in S}\frac{(t^-_{sm}+t^+_{sm})}{t_{sm}} - \alpha_3 \sum_{z\in Z} w_z \sum_{l=1}^{L}\left(UU_{z,l}+OU_{z,l}\right) \quad (1)$$

- Constraints:

$$\sum_{s\in S} x_{smwdbr} \le 1 \;\; \forall\, m\in M, w\in W, d\in D, b\in B, r\in R \quad (2)$$

$$2\sum_{r\in R} x_{smwdbr} \le \sum_{i\in I} a_{ismwdb} \;\; \forall\, s\in S, m\in M, w\in W, d\in D, b\in B \quad (3)$$

$$2\sum_{b\in B}\sum_{r\in R} x_{smwdbr} \le d_{sd} \;\forall\, s\in S, m\in M, w\in W, d\in D \quad (4)$$

$$2\sum_{d\in D}\sum_{b\in B}\sum_{r\in R} x_{smwdbr} \le \sum_{i\in I} ww_{is} \;\forall s\in S, m\in M, w\in W \quad (5)$$

$$\sum_{r\in R} x_{smwdbr} \le \sum_{a\in A} a_{amwdb} \;\; \forall\, m\in M, w\in W, d\in D, b\in B \quad (6)$$

$$\sum_{b\in B}\sum_{r\in R} x_{smwdbr} \le da_d \forall\, m\in M, w\in W, d\in D \quad (7)$$

$$\sum_{s\in S}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R} x_{smwdbr} \le \sum_{a\in A} ww_a \;\forall\, m\in M, w\in \quad (8)$$

$$t^-_{sm}, t^+_{sm} \ge 0 \;\; \forall\; s\in S, m\in M \quad (9)$$

$$x_{smwdbr} \in \{0,1\} \;\forall\, s\in S, m\in M, w\in W, d\in D, b\in B, r\in R \quad (10)$$

$$\sum_{w\in W}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R}(x_{smwdbr} * \mathrm{asd}_s) + t^-_{sm} - t^+_{sm} = t_{sm} \;\; \forall\, s\in S, m\in M \quad (11)$$

$$t^-_{sm} \le M \times (1-w_{sm}) \;\forall\, s\in S, m\in M \quad (12)$$

$$t^+_{sm} \le M \times w_{sm} \;\forall\, s\in S, m\in M \quad (13)$$

$$\sum_{w\in W}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R} x_{smwdbr} \ge 1 \quad \forall\, s\in S, m\in M \quad (14)$$

$$x_{smwdbr} - x_{s,m,w=1,d,b,r} = y^+_{smwdbr} - y^-_{smwdbr} \;\forall\, s\in S, m\in M, w\in W, d\in D, b\in B, r\in R \quad (15)$$

$$y^+_{smwdbr} + y^-_{smwdbr} \le 1 \;\forall\, s\in S, m\in M, w\in W, d\in D, b\in B, r\in R \quad (16)$$

$$y^+_{smwdbr}, y^-_{smwdbr} \,\epsilon\, \{0,1\} \qquad \forall\, s\in S, m\in M, w\in W, d\in D, b\in B, r\in R \quad (17)$$

$$\sum_{s\in S}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R}(y^+_{smwdbr}+y^-_{smwdbr}) \le \Delta_w \qquad \forall\, m\in M, w\in \{2\ldots, W\} \quad (18)$$

$$x_{smwdbr} - x_{s,m=1,,w,d,b,r} = j^{+}_{smwdbr} - j^{-}_{smwdbr} \ \forall\, s \in S, m \in M, w \in W, d \in D, b \in B, r \in R \tag{19}$$

$$j^{+}_{smwdbr} + j^{-}_{smwdbr} \leq 1 \quad \forall\, s \in S, m \in M, w \in W, d \in D, b \in B, r \in R \tag{20}$$

$$j^{+}_{smwdbr}, j^{-}_{smwdbr} \in \{0,1\} \quad \forall\, s \in S, m \in M, w \in W, d \in D, b \in B, r \in R \tag{21}$$

$$\sum_{s\in S}\sum_{w\in W}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R} j_{smwdbr} \leq \Delta_m \ \forall\, m \in \{2, \dots, M\} \tag{22}$$

$$F^{z}_{sl} = \sum_{b\in B}\sum_{r\in R} \lambda_s \left(\sum_{k=0}^{N_s-1} x_{s,m,\mu,\tau,b,r} \ \ e_{s,k+1} \right) \forall\, s \in S, m \in M, z \in Z, l \in \{N^{z}_{s}, \dots, L_m\} \tag{23}$$

$$F^{z}_{sl} = \sum_{b\in B}\sum_{r\in R} \lambda_s \left(\sum_{k=0}^{l-1} x_{s,m,\mu,\tau,b,r} \ \ e_{s,k+1} \right) \forall\, s \in S, m \in M, z \in Z, l \in \{1, \dots, N^{z}_{s}\} \tag{24}$$

$$\bar{F}^{Q}_{l} = \sum_{s\in S} F^{Q}_{sl} \ \ \forall\, s \in S, l \in L_m \tag{25}$$

$$\bar{F}^{I}_{l} = \sum_{s\in S} F^{I}_{sl} \ \ \forall\, s \in S, l \in L_m \tag{26}$$

$$\bar{F}^{W}_{h,l} = \sum_{s\in S_h} F^{W}_{sl} \ \ \forall\, s \in S, l \in L_m, h \in H \tag{27}$$

$$U_{z,\ell} - UU_{z,\ell} \leq \ \bar{F}^{z}_{l} \leq U_{z,\ell} + OU_{z,\ell}, \qquad z \in \{Q, I, H\}, \ell \in \mathcal{L} \tag{28}$$

$$U_{z,\ell} + OU_{z,\ell} \leq \ C_{z,\ell}\,, \qquad z \in \{Q, I, H\}, \ell \in L_m \tag{29}$$

Constraints (2)-(29) can be organized in 4 sets: operational constraints (2) – (10), constraints to balance supply and demand (11) – (14), constraints to promote stability to the MSS (15) – (22), and up- and downstream constraints (23) – (29).

IV. Application to Hospital Espírito Santo de Évora

The model is implemented using the software General Algebraic Modeling System (GAMS). GAMS "is a high-level modeling system for mathematical programming and optimization, that consists of a language compiler and a stable of integrated high-performance solvers, tailored for complex, large scale modeling applications, that allows the user to build large maintainable models that can be adapted quickly to new situations" (GAMS website, 2016). However, it showed some limitations to implement constraints (23) and (24). Thus, the implementation of the model includes only the first two objectives of the objective function: maximization of the allocated slots and its aggregated preferences and the minimization of the deviation from the target. This limitation is related with limitations of the used software and inability of implementing the constraint represented by constraints (23) and (24), as well as a minor interest from the hospital to implement the third objective. All the tests are performed on an Intel® Core™ i5-7200U CPU @ 2.50GHz processor with the Windows 10 operating system. Subsection 1 performs a normalization of the objective function, subsection 2 presents a comparison of the results with the MSS of the case study and subsection presents some conclusion.

1) Normalization of the objective function

To normalize the objective function, it is used a known technique which consists of three steps. First, the maximum and minimum value of each of the objectives are calculated. To this end each objective is optimized individually to find the maximum value of the optimized objective and the minimum value of the excluded objective. Then each objective is subtracted by its minimum value and divided by the difference between the maximum and minimum values, as generally represented in expression (30). Finally, the normalized terms are summed up to a single objective. The new objective is dimensionless.

$$\frac{f(x) - f^{min}}{f^{max} - f^{min}} \tag{30}$$

In this case, it is not possible to optimize the two objectives individually as the second objective depends on the first. Therefore, each objective function is individually optimized by giving a weight close to one to the objective to be optimized and close to zero to the other objective. To simplify the description, objective two is analyzed as a negative objective. Meaning that the new objective (t_2) is equal to the symmetric of the second objective (z_2): $t_2 = -z_2$. Table 21 shows the weights (α_1, α_2) given to the two objectives and the respective values.

	α_1	α_2	*Optimum value*	*Minimum value*	*Domain range*
Objective 1(z_1)	0,9999	0,0001	4104,689	3621,286	483,4
Objective 2(t_2)	0,0001	0,9999	-30,317	-69,848	39,531

As shown in Table 21, the minimum value for objective 1 is 3621,286 and for objective 2 is -69,848, and differences between the maximum and the minimum are 483,4 and 39,531, respectively, resulting in objective function (31):

$$\max \alpha_1 \frac{\sum_{s\in S}\sum_{w\in W}\sum_{d\in D}\sum_{b\in B}\sum_{r\in R}\left(\frac{\sum_{i\in I} k_{isdb}}{|i|}+\frac{\sum_{a\in A} k_{adb}}{|a|}\right)x_{smwdbr} - 3621,286}{483,4} + \alpha_2 \frac{\sum_{s\in S}(t_{sm}^{-}+t_{sm}^{+})/t_{sm} + 69,848}{39,531} \quad (31)$$

2) Comparison of the proposed MSS with the current MSS

HESE's MSS has been nearly the same for the last 30 years, with the same schedule, planning and organization. Although the MSS hasn't changed, the workforce and the demand is constantly changing. This results in a bad allocation of the resources as the schedule does not follow the patients' needs and of the health staff. This bad allocation means the allocation of a slot to a specialty, and later the non-occupation of it this slot by the allocated specialty. This happens due to the shortage in anesthesiologists, surgeons and nurses, due to delays in surgeries or no-show of the patients. This model is not capable of improving surgeries delays or no-show of patients but can reduce the shortages, as it allocates the specialties to slots having in consideration the workforce availability.
The hospital data shows:

- the number of surgeons and anesthesiologists varied during 2017;
- there are last minute changes that sometimes are not submitted to the monitoring of the OR;
- some surgeries had exceptions in terms of number of surgeons in the OR during the surgical intervention (some operations occurred with only one surgeon).

These facts can compromise the comparison of the results. However, it is possible to observe that the OR needs a tool to help in allocating the available resources. Tables 2 and 3 show the number of slots, in 2017, which are allocated to the specialties (Table 2) and the number of slots which are in fact occupied (Table 3). In some specialties, the no utilization of the slots reaches 50% of the allocated slots, and stomatology is the only specialty that has utilized all its slots. This results in waste of resources since the staff which is ready to operate on that day could be allocated to other activities. As the model takes into consideration the number of resources in each month, week and day, the results should be compared with Table 3, as reflects the real occupation of the slots.

Table 1 - Number of allocated slots in 2017

Specialty/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
General Surgery	40	34	40	27	32	35	32	13	25	33	28	20
Plastic Surgery	9	7	9	6	8	6	4	2	4	7	5	3
Pediatric Surgery	4	4	5	4	5	4	3	1	3	4	3	3
Stomatology	1	1	1	1	0	1	1	0	1	1	1	0
Ophthalmology	26	22	27	14	23	21	14	3	17	25	19	14
Orthopedics	20	19	21	13	16	13	15	8	12	21	19	10
ORL	8	8	10	4	7	5	5	2	5	7	5	2
Urology	9	8	9	8	7	5	6	3	2	7	5	1

Table 2 – Number of occupied slots in 2017

Specialty/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
General Surgery	28	25	29	27	32	35	32	13	25	25	16	15
Plastic Surgery	6	7	7	6	8	6	4	2	4	5	4	0
Pediatric Surgery	4	4	3	4	5	4	3	1	3	4	1	3
Stomatology	1	1	1	1	0	1	1	0	1	1	1	0
Ophthalmology	20	22	22	14	23	21	14	3	17	23	15	6
Orthopedics	18	15	17	13	16	13	15	8	12	18	12	7
ORL	3	6	7	4	7	5	5	2	5	7	3	1
Urology	8	7	7	8	7	5	6	3	2	7	3	1
Total	88	87	93	77	98	90	80	32	69	90	55	33

Table 4 shows one of the obtained solutions in order to compare the two MSS

Table 3 – Obtained MSS with the best value for the objective function

Specialty/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
General Surgery	32	32	32	32	32	32	32	32	32	32	32	32
Plastic Surgery	8	8	8	8	8	8	8	8	8	8	8	8
Pediatric Surgery	3	4	3	3	4	3	4	3	3	3	4	4
Stomatology	1	1	1	1	1	1	1	1	1	1	1	1
Ophthalmology	20	20	20	20	20	20	20	20	20	20	20	20
Orthopedics	8	8	8	8	8	8	8	8	8	8	8	8
ORL	8	8	8	8	8	8	8	8	8	8	8	8
Urology	8	8	8	8	8	8	8	8	8	8	8	8
Total	88	89	88	88	89	88	89	88	88	88	88	88

Looking at the month of January it is possible to conclude that with the same number of allocated slots (88), the model suggests another distribution among the specialties. The biggest differences are in general surgery and orthopedics – the model increases the number of slots in general surgery and decreases the number of allocated slots to orthopedics, in order to better match supply and demand. The differences in terms of the number of operated patients are depicted in Table 5. Table 5 suggests that supply is better suited to the demand in model's suggestion. The difference between the percentage of the supplied demand of general surgery and orthopedics is higher in HESE's distribution of the operating room time ($10{,}50\% - 6{,}30\% = 4{,}25; 7{,}20\% - 4{,}70\% = 2{,}5\%$).

In the other months, it is clear that HESE has some difficulties in maintaining the normal schedule, having a lot of fluctuation in the number of allocated slots, reaching, sometimes, better numbers than the allocation made by the model. These fluctuations are more pronounced in some specialties as general surgery that reaches differences of 10 slots.

Table 4 – Comparison of the distribution of operating room time between the current MSS and model's suggestion

Indices	MSS	Specialty	
		General Surgery	Orthopedics
Number of slots	HESE	28	18
	Model	32	8
Number of operated patients	HESE	$28 \times \lambda_s = 28 \times 2 = 56$	$18 \times \lambda_s = 18 \times 3 = 54$
	Model	$32 \times \lambda_s = 32 \times 2 = 64$	$8 \times \lambda_s = 8 \times 3 = 24$
Demand		$888\ patients$	$514\ patients$
Percentage of the demand	HESE	$\frac{56}{888} = 6{,}30\%$	$\frac{54}{514} = 10{,}50\%$
	Model	$\frac{64}{888} = 7{,}20\%$	$\frac{24}{514} = 4{,}70\%$

This analysis is made varying the parameters that guarantee stability. Tables 6 and 7 present the number of surgeons that HESE's could have to fill all the available slots. Table 7 presents the number of surgeons, variable over the year, in order to better reach the demand. Table 6 does not allow changes over the year, suggesting only one number of surgeons for the whole year. The numbers suggested by the model can also be used to calculate the proportionality of required surgeons between the specialties. As the model suggests a proportionality of the workforce, HESE can maintain the same number of surgeons but changing the distribution of them as depicted in Table 8.

Table 5 – suggested distribution of the surgeons with $\Delta_m = 0$

Specialty		Actual	Prop.
General Surgery	20	14	29%
Plastic Surgery	4	2	6%
Pediatric Surgery	2	2	3%
Stomatology	2	2	3%
Ophthalmology	12	10	17%
Orthopedics	16	5	23%
ORL	6	4	9%
Urology	8	4	11%
Total	80	43	

Table 6- suggested distribution of the surgeons to fill all the slots of the MSS $\Delta_m = 20$

Specialty	Max	Min	Actual
General Surgery	24	20	14
Plastic Surgery	4	2	2
Pediatric Surgery	2	2	2
Stomatology	2	2	2
Ophthalmology	14	12	10
Orthopedics	16	14	5
ORL	6	6	4
Urology	8	8	4
Total	86	78	43

Table 7 – suggested distribution of surgeons maintaining the total number of surgeons

Specialty	Actual	Sugg.
General Surgery	14	12
Plastic Surgery	2	2
Pediatric Surgery	2	2
Stomatology	2	2
Ophthalmology	10	7
Orthopedics	5	10
ORL	4	4
Urology	4	5
Total	43	44

3) Discussion

This section validates and discusses the results obtained by using the proposed model, maximizing the objective function composed by the first two objectives: maximize the number of allocated slots and their associated aggregated preferences and minimize the difference between the number of allocated slots per specialty s and its target t_s. It is possible to conclude that this model can be used as a tool to flexible resource allocation (i.e. operating room time allocation among the specialties) according to the variability in surgical demand and availability of staff (tactical decision) and to perform sensitive analysis to understand the consequences of variations in strategic decisions (e.g. staff capacity dimensioning). Due to shortages in anesthesiologists, surgeons and nurses, some allocated slots are left empty decreasing the efficiency and effectiveness of the SS. The model is able to allocate specialties to slots considering the availability of the health clinical staff for each month, week and day allowing a better allocation over the year. Furthermore, it is possible to conclude that the model suggests another distribution of the slots, allocating more slots to the specialties with greater higher surgical demand.

V. Conclusions

Hospitals depend on their SS as this unit represents more than 40% of hospitals costs and profits and are usually considered in the literature as the engine of the organization (Beliën & Demeulemeester, 2007; Blake & Donald, 2002). As analyzed in the literature review, the complexity of this unit is not only related with planning of different surgeries with different patients within the same physical and scarce space, but also with the large amount of other up and downstream services that it compromises.

In this work, the case study challenges were analyzed and studied with tools suggested by the literature and with the experience of the involved stakeholders. Based on the collected data and on the existing literature, this work develops a multi-objective MILP model that captures the case study needs by structuring the planning of SS and by supporting the hospital understudy on the strategic-tactical decision making. The model constructs a new MSS which aims to be more effective and efficient on the allocation of HESE's resources. Efficiency is one of the major objectives since HESE is a small hospital with low financial resources, that needs to be efficient in other to handle its demand.

Furthermore, this work contributes to the literature by integrating objectives which according to this work literature review have never been studied together. These objectives promote an MSS which gathers the maximization of the allocated slots with an allocation directed towards a better match between supply and demand, meaning an allocation based on the percentage of the surgical waiting list. The model uses one year of planning horizon, which allows a more fitted allocation of the slots to the demand. To accomplish this adjustment, the model develops a non-cyclical MSS not very common in the literature. The non-cyclicity allows the incorporation of the staff availability in all weeks and months, allowing a projection of the effects of staff shortages or vacations. Moreover, for a better implementation of the new MSS, this model embodies objectives as the maximization of the stakeholders' preferences and the stability of the SS master schedule.

All in all, this work proposes a model to better allocate operating room time among the surgical specialties, considering

HESE's workforce, SS space and the surgical demand. To evaluate the developed model comparisons are made on the number of allocated slots. Results showed that the model cannot allocate a bigger number of slots than HESE, in turn, suggests a different distribution of slots. This different distribution improves the matching between supply and demand, not by increasing the total number of operated patients but, by allocating more slots to those specialties with larger waiting lists. Moreover, this model potentially improves the efficiency of the SS by including the availability of surgeons and anesthesiologists in every month, week, day and shift, helping in predicting future shortages, and consequently avoiding empty allocated slots.

Results allow to conclude that the workforce greatly restricts a higher match of the demand. For this reason, another analysis is made on the distribution of surgeons by the specialties, suggesting another distribution with the same number of surgeons and for future larger workforces.

Some interesting points are left to future work.

One of the major challenges of this study is to match supply and demand. The developed tool allows to plan the SS activities with one year in advance, suggesting a variation on the number of slots allocated to each specialty. This variation changes surgeons' agenda and the number of hours each one dedicates to the SS. An interesting study would be to adjust and analyze the trade-off between the number of hours a surgeon spends in the operating room and in consultations. Another open point is the assessment of the preferences. It would be interesting to change the aggregated preferences to singular preferences, maximizing each anesthesiologist and surgeon preference and not off the entire specialty. Finally, the last objective, to level the utilization of up- and downstream resources, hasn't been implemented due to software restrictions. Despite the limited interest of the hospital on this topic, the validation and implementation of this objective could lead to new perspectives on the planning of HESE's SS.

VI. References

Agnetis, A., Coppi, A., Corsini, M., Dellino, G., Meloni, C., & Pranzo, M. (2012). Long term evaluation of operating theater planning policies. *Operations Research for Health Care*, *1*(4), 95–104.

Beliën, J., & Demeulemeester, E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. *European Journal of Operational Research*, *176*(2), 1185–1204.

Blake, J. T., Dexter, F., & Donald, J. (2002). Operating room managers' use of integer programming for assigning block time to surgical groups: A case study. *Anesthesia and Analgesia*, *94*(1), 143–148.

Brandeau, M. L., Sainfort, F., & Pierskalla, W. P. (2004). *Operations Research and Health Care a Handbook of Methods Operations Research & Management Science*.

Day, R., Garfinkel, R., Thompson, S., Day, R., Garfinkel, R., & Thompson, S. (2012). Integrated Block Sharing : A Win – Win Strategy for Hospitals and Surgeons. *Manufacturing & Service Operations Management*, *14*(4), 567–583.

Dellaert, N., & Jeunet, J. (2017). A variable neighborhood search algorithm for the surgery tactical planning problem. *Computers & Operations Research*, *84*, 216–225.

Fei, H., Meskens, N., & Chu, C. (2010). A planning and scheduling problem for an operating theatre using an open scheduling strategy. *Computers and Industrial Engineering*, *58*(2), 221–230.

Liu, Y., Chu, C., & Wang, K. (2011). A new heuristic algorithm for the operating room scheduling problem. *Computers & Industrial Engineering*, *61*(3), 865–871.

Malik, M. M., Khan, M., & Abdallah, S. (2015). Aggregate capacity planning for elective surgeries: A bi-objective optimization approach to balance patients waiting with healthcare costs. *Operations Research for Health Care*, *7*, 3–13.

Penn, M. L., Potts, C. N., & Harper, P. R. (2017). Multiple criteria mixed-integer programming for incorporating multiple factors into the development of master operating theatre timetables. *European Journal of Operational Research*, *262*(1), 194–206.

Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., & Rademakers, F. E. (2016). Scheduling operating rooms: achievements, challenges and pitfalls. *Journal of Scheduling*, *19*(5), 493–525.

Santibáñez, P., Begen, M., & Atkins, D. (2007). Surgical block scheduling in a system of hospitals: An application to resource and wait list management in a British Columbia health authority. *Health Care Management Science*, *10*(3), 269–282.

Yahia, Z., Harraz, N., & Eltawil, A. (2014). Operating Room Scheduling Problems: A Survey and a Proposed Solution Framework. In *Transactions on Engineering Technologies* (pp. 717–731).

Zhang, B., Murali, P., Dessouky, M. M., & Belson, D. (2009). A mixed integer programming approach for allocating operating room capacity. *Journal of the Operational Research Society, 60*(5), 663–673.