Optimization of Operations in the Surgical Service: Surgery Scheduling in a Hospital Context

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Abstract

The Operating Room (OR) holds a significant amount of a hospital's total costs and revenues. Thus, an efficient management, easily translates into an efficient and profitable health facility and improves the healthcare provided there. Scheduling is a central activity in an OR, as it determines how the OR will function, for a certain planning period. In the case study hospital, a new and improved OR scheduling technique is expressed by the staff, as essential currently. With that in mind, in this work, a deterministic Integer Linear Programming (ILP) model is developed, to optimize the OR scheduling of elective surgeries, aiming at maximizing the number of surgeries scheduled, the profit and the balance between the MSS and the surgeon's preferences. The model considers the room capacity, human resources capacity (nurses and anesthesiologists), type of rooms and downstream unit capacity. This study contributes to the literature with the integration between following tactical decisions made by the hospital and attending the surgeon's preferences. The introduction of the surgeon's preferences as an objective and the inclusion of day, hour, nursing team and anesthesiologist in these, represents a novel feature. The exact solution obtained, using real data, successfully integrates the surgeon's preferences and the MSS, in the schedule. The results also highlight the main management changes necessary in the service, which also constrained the application of the model to real data.
Keywords: Operating Room, Surgery Schedule, Preferences, Master Surgery Schedule, Linear Programming.

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1. Introduction

A surgical service has a significant impact in the hospital's management. The surgical center is considered the most costly functional area in a hospital, and an Operating Room (OR) can account for an estimate of 10-30% of the total hospital expenditures [7]. It is estimated that the OR can be responsible for approximately 40% of a hospital's total revenue [3]. Therefore, it can be assumed that an efficient OR significantly contributes to an efficient and profitable health facility. This directly improves the quality of the healthcare provided, which represents the ultimate goal. Due to the significant influence the OR management has over the hospital's financial state, OR planning and scheduling have been intensively addressed in the literature, to attempt at optimizing these issues, which need continuous improvement. Mainly because health activities are extremely sensitive, as they include the patient's interest and health status, and not just the management interest of the institution. Therefore, more abrupt optimization changes, that can be implemented in other types of services, are not advised in the health sector. In addition, there is no general strategy, that can be globally applied to every health facility, that optimizes the OR planning and scheduling. Each strategy has to be accurately applied and adjusted to the hospital in study, since each OR has its own goals, issues and constraints associated. Finally, optimizing health activities can be constrained by implemented strategies based on the professionals experience, that usually don't optimize the operations. However, when introducing a new strategy, the staff has to be considered, since their satisfaction is a major factor to provide the proper care to the patients.

This work aims at optimizing the OR scheduling of elective surgeries, in the case study hospital, by developing a scheduling strategy, taking into consideration tactical decisions made by the department administration. With that in mind, a deterministic Integer Linear Programming (ILP) model is created, after assessing the hospital's needs and goals. The final schedule must optimize the balance between following the surgeon's preferences and following the hospital's Master Surgery Schedule (MSS). The relevant OR scheduling studies can be mainly divided according to the decision levels and the tactical and operational are the ones considered. From the tactical point of view, there is the MSS, which consists in, essentially, assigning time blocks to surgical specialties, in a planning period, usually cyclical. In this study, tactical decisions are not made, but are taken into consideration, as well as its execution. The operational level decisions include selection of patients from a waiting list, assignment of surgeon, room and date (day and hour) to perform the surgeries. This study includes all the operational decisions mentioned, having initially as a waiting list, the surgeries to schedule in a week, and assigning a team and a date to each surgery selected. Since emergency surgeries are not taken into consideration, and operational decisions are made, this study falls in the category of *Elective Surgery Scheduling*.

This study's contribution is mainly concerned with the objectives of the model. The surgeon's preferences inclusion is the main novel feature in the study, because although previously included in the literature, it is not found an optimization mathematical model that handles the surgeons preferences similarly to this study. First, most studies that consider the surgeons preferences, only do that in terms of staff affinity, and these are included in the constraints [16][8]. There are cases in which the surgeon's preferences are considered, in terms of starting hours for their surgeries, and introduced as a constraint in the model [14]. The surgeon's preferences are included as an objective, in [11], in which the preferable days, hour and even time blocks, are collected for each surgeon. However, this feature is not successfully introduced. In the present work, these preferences include day, hour, nursing team and anesthesiologist requests, all present in an objective.

The next section contains the case study description and the third reviews the topic concerning what is found in the literature. The fourth section details the model implemented. In the fifth the numerical experiments and the hospital validation are discussed. Finally, in the last section, conclusions, limitations and future work are assessed.

2. Contextualization

This surgical service occupies three floors of the hospital, two of them having the 8 existing operating rooms, and, in all, there are bedrooms. However, currently, only 5 rooms are open. Additionally, OR2 and OR3 are treated as one in terms of scheduling. Therefore, in practical terms, 4 rooms are available and this decision is made based on human resources constraints, mainly in terms of anesthesiologists. The service is working 14 hours a day, 6 days a week. Currently, the utilization rate is estimated to be around 40%, and although this is a low value, this concept is complicated, since a high utilization doesn't always mean a higher profit is generated. The OR may rather have less surgeries being performed, but for which profit margins are higher, and that is in fact, the case of this OR.

It was lastly counted 186 surgeons teams. It is clear that all these teams can't be regular in this OR, since this number is extremely high, and inconsistent with the OR's utilization. Although no record is kept of how many of these teams are external (the ones that only go to hospital when they have a surgery scheduled), this number indicates the uncontrolled access of external surgeons to this OR. Theoretically, the external surgeons' schedule can be altered, as there is no contract defining their time block assignment. However, this is not happening, mainly because these teams have been working with the hospital for a long time, their preferable hours started to become usual and these teams are not willing to change their schedule. This causes overlapped preferential schedules, while there is available rooms in other hour within the same day, for example. Considering the nursing staff, 30 nurses are currently hired, although about 20% of them are not working, due to health issues or maternity leaves. The administration of the surgical service estimated that an extra 12 nurses are needed in order to have an efficient service.

When a non-elective patient appears and has to undergo surgery in a situation of emergency or urgency, if necessary, the daily schedule is changed to fit the surgery, according to its level of urgency. However, the case-volume of non-elective surgeries is significantly low. Therefore, the current way to handle the emergencies is suitable to the case study.

On the other hand, to schedule an elective surgery, a surgical proposal has to be submitted by the surgeon, where the date and hour is required, as well as the material and team necessary. However, in many cases, surgeons try to schedule their surgeries without the proper anticipation, through different paths. The department administration approves the weekly schedule by the end of the previous week, in which the downstream resources and surgical teams' availability are revised and changes are made, if necessary. The OR has a MSS built by the administration to determine each surgical specialty weekly time blocks, which has restricted the time for external surgeons and, even for the internal surgeons, their requests are often neglected.

To try to solve, simultaneously, the highest number of detected issues, optimizing the surgery scheduling might by the right path. By providing a new scheduling strategy, it is possible to improve issues related with the utilization rate, uneven OR use, external surgeon's scheduling issues, surgical proposals issues and lack of MSS compliance. Solving other mentioned issues, such as the deficit in terms of human resources, involves decisions from the administration, however the use of the existent human resources can be optimized with a scheduling optimization technique. Ideally, the staff satisfaction and following the MSS, surgical proposal strategy and other tactical decisions made by the hospital, should be combined towards their improvement, leading to the OR operations optimization.

3. Literature Review

As concluded in the previous section, the main concern is surgery scheduling, highly investigated, since it includes key problems in the OR management. These problems can be mainly divided according to the decision level associated: strategic, tactical and operational. However, strategic level decisions are not included in the scope of this work and the operational level is its main focus. Within the operational level, the planning problem (or *Advance Scheduling*) includes availability of OR and surgeon to allocate a date to each patient's procedure, while scheduling (or *Allocation Scheduling*) defines the daily procedure sequence for each OR, according to human and material resources' availability [8].

Some studies aim at solving both operational problems simultaneously, using both exact and heuristic solution methods, including decisions from *Advance* and *Allocation Scheduling*. The heuristic methods are applied to improve the exact method's performance, when these can't reach a solution. Multiple objectives are common in scheduling optimization models, and objectives like maximizing OR utilization and minimizing cancellations have been combined [4]. Tardiness and idle time minimization are associated with the number of surgeries scheduled [9] and also with overtime minimization [15]. Minimizing costs is the most common objective in OR optimization studies [17]. [13] aims at minimizing makespan, also commonly considered. The human resources capacity as a constraint in scheduling optimization models, is not recent, and can be considered standard when solving planning and scheduling problems. [4] includes not only human resources, but also the downstream unit capacity, with special focus on weekend capacities for all resources. [13] also consider the downstream unit capacity, together with the operating rooms capacity. Human and material resources capacity are introduced as constraints in [15] and [9], but in the last, room eligibility for each procedure is also included. The models are often tested with real data, and specifically applied to a hospital or health facility case study, like in [4] and in [13]. Mixed Integer Linear Programming (MILP) models are developed in [9][15][17], a case of Integer Linear Programming (ILP) models, which is developed in [4]. [13] solve the problem through a Mixed Integer Programming (MIP), also similar.

The *Advance Scheduling* has also been addressed individually, mainly through ILP again, such as in [2] [10] and [6]. Exact solving methods are utilized in [10] and [6], while [2] add an heuristic technique to enhance the model's performance, due to extensive computational times. In [6] a systematic approach to change the scheduling policy in a Portuguese hospital is proposed. The main goals include OR throughput maximization, and enhance the equity and access to patients, mainly by minimizing waiting times, while considering levels of clinical priority. The model is developed for three different versions: the administration's, the surgeon's and a mixed version, each translating the correspondent stakeholder's point of view. In [2] is developed a Decision Support System for a Spanish hospital, to assist OR scheduling. The model maximizes a service quality indicator, which balances the achievement of standards imposed for all hospitals and the clinical priority of each patient. As constraints, human resources and the patient's availability are taken into consideration. After defining the MILP model, three heuristics are defined to help solve it.

Allocation Scheduling is also isolated and solved. MILP approaches are used in [1], [12] and [5]. In the last, a Constraint Programming (CP) technique is also developed. [16] use MIP, also combined with CP to solve the scheduling problem. Only [12] handle the problem using just exact solving methods, while [1], [5] and [16] add an heuristic to improve the solution quality and running time. The model from [1] considers up and downstream units' capacities. The objectives include: prioritizing patients that have already been canceled once or that the surgeon prefers to operate first, embody the residence-hospital distance so that the ones further are not scheduled in the first morning slot, minimize the length of stay of each patient and level the bed occupancy, to reach an also leveled staff workload. In [12], the model includes the surgeons' idle times, type of surgeon, potential overtime and operating room use. Aiming to minimize costs, the model is applied to a teaching hospital. In [16], a comparison between MIP and CP approaches, to solve the daily scheduling problem, is presented. Surgeon, nurse and anesthesiologist availability, opening and closing hours of the OR, equipment quantity, downstream resources, affinity between staff members, translated into a score and priority levels are considered in the constraints. Both models minimize the time gaps in the schedule and in the MIP one the constraints are linearized, which doesn't guarantee the model's effectiveness. The CP model, by having a higher number of constraints, finds optimal solutions slower, but shows more efficiently the feasible ones. Later, [5] use the MILP to solve small instances and the CP with an heuristic method to large ones. The main characteristic of this study is the inclusion, for the first time found in the literature, of all resources necessary for a surgery (human, material and facilities), downstream unit resources and possible emergency cases. The objective is makespan minimization, by minimizing closing time of the last room being used.

According to the literature found, heuristic methods only have to be implemented, when the exact methods are not enough to reach an optimal solution. There are aspects that are commonly considered, and therefore, need to be included in this work. The human resources capacity and the room capacity are two of these cases that are commonly included in the constraints. ILP is commonly utilized when solving operational scheduling problems, being MILP the most used. Concerning the objectives, these are not chosen according to the literature tendency, only considering the case study situation. However, it is important to know which objectives are usually utilized to know if there is a possible contribution to the literature in this work. Minimizing costs can be considered the most used objective, but it is not mentioned as a concern by the stakeholders. The main goal in the developed model will be to find a balance between maximizing the surgeon's preferences and maximizing the MSS compliance. This also represents the main contribution of this work to the literature.

4. Mathematical Model

This ILP model considers the tactical decisions, namely the MSS, built by the head staff of the service. It schedules the surgeries for a week, having as waiting list the surgeries to be scheduled in that period. The model has multiple objectives, the first being maximizing the number of scheduled surgeries and the second maximizing the profit. The third objective balances the surgeon's preferences maximization and the MSS compliance. The surgeon's preferences are translated into the requested surgical team, day and timeslot for the surgery. This objective is controlled with weights, allowing to change the flexibility of both components.

4.1. Notation and Assumptions

For each specialty, the internal and external surgeons are considered to belong to two different specialties and schedule differently. Cancellations, extra hours and delays are not included and the pair surgeon-surgery is assumed defined, since the surgeon requests the surgery. The material resources availability is also assumed. Usually, a common surgery is performed by the responsible and the assistant surgeons. However, assistant surgeons are considered available, and are not included in the schedule built, since these are not a constraint in surgery scheduling. In **Table 1** the model's notations is summarized.

Table 1: Notation

Sets and Indices	
$s \in S$	surgeries to be scheduled in the next week
$c \in C$	surgeons to perform the surgeries in S
$a \in A$	anesthesiologists
$n \in N$	nurses that are able to scrub in the surgery
$d \in D$	days of the week
$r \in R$	operating rooms
$t \in T$	daily timeslots
$e \in E$	surgical specialties
Subsets	
$S_b \subseteq S$	surgeries that require a bed in the postoperative unit
$C_s \subseteq C$	surgeon responsible for surgery s
Parameters	
ba	number of beds available in downstream unit
d_s	duration estimate for surgery s, according to hospital estimate, in number of timeslots
nn	number of needed nurses to assist in a surgery
p_s	profit margin concerning surgery s
k_1	weight of objective that maximizes surgeon satisfaction
k_2	weight of objective that maximizes MSS compliance
ν_{edtr}	1 if surgical specialty e is allowed to be scheduled in day d, timeslot t and operating room r, 0 otherwise
θ_{se}	1 if surgery s belongs to specialty e, 0 otherwise
σ_{dr}	1 if room r is open in day d, 0 otherwise
ζ_{er}	1 if surgical specialty e can be scheduled in room r due to fixed material, 0 otherwise
μ_{sdt}	1 if surgery s was asked for day d, timeslot

	t by the surgeon responsible, 0 otherwise
μ_{asdt}	1 if anesthesiologist a was asked for surgery s, in day d, timeslot t, by the surgeon responsible, 0 otherwise
μ_{nsdt}	1 if nurse n was asked for surgery s, in day d, timeslot t, by the surgeon responsible, 0 otherwise
Auxiliary Variables	
δ_{csdt}	1 if surgeon c performs surgery s in day d in timeslot t, 0 otherwise
α^{start}_{sdtr}	1 if surgery s is scheduled to start in timeslot t, room r, day d, 0 otherwise
λ^{start}_{asdt}	1 if anesthesiologist a starts surgery s in day d in timeslot t, 0 otherwise
β^{start}_{nsdt}	1 if nurse n starts surgery s in day d in timeslot t, 0 otherwise
Decision Variables	
α_{sdtr}	1 if surgery s is scheduled for weekly day d and timeslot t to occupy operating room r, 0 otherwise
λ_{asdt}	1 if anesthesiologist a performs surgery s in day d in timeslot t, 0 otherwise
β_{nsdt}	1 if nurse n performs surgery s in day d in timeslot t, 0 otherwise

4.2. Numerical Model

In this section, the ILP model is presented.

$$\max \quad \sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\alpha^{start}_{sdtr} \tag{1}$$

$$\max \quad \sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R} p_s \times \alpha^{start}_{sdtr} \tag{2}$$

$$\begin{aligned}\max \quad & k_1\Big(\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\mu_{sdt}\times\alpha_{sdtr}+\\ &+\sum_{a\in A}\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\mu_{asdt}\times\lambda_{asdt}+\\ &+\sum_{n\in N}\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\mu_{nsdt}\times\beta_{nsdt}\Big)+\\ &+k_2\Big(\sum_{s\in S}\sum_{e\in E}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\theta_{se}\times\\ &\times\nu_{edtr}\times\alpha_{sdtr}\Big)\end{aligned} \tag{3}$$

$$\text{s.t.}: \sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\alpha^{start}_{sdtr}\leq 1, \quad \forall s\in S \tag{4}$$

$$\sum_{s\in S}\alpha_{sdtr}\leq\sigma_{dr}, \quad \forall d\in D, t\in T, r\in R \tag{5}$$

$$\alpha_{sdtr}\geq\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, t\in T, r\in R \tag{6}$$

$$\alpha_{sdtr}\leq\theta_{se}\times\zeta_{er}, \quad \forall s\in S, d\in D, t\in T, r\in R, e\in E \tag{7}$$

$$\sum_{d\in D}\sum_{r\in R}\alpha^{start}_{sdtr}=0, \quad \forall s\in S, t=\mid T\mid-d_s+1,...,\mid T\mid \tag{8}$$

$$\sum_{t'=t}^{t+d_s-1}\alpha_{sdt'r}\geq d_s\times\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, r\in R, t=1,...,\mid T\mid -d_s+1 \tag{9}$$

$$\sum_{t\in T}\alpha_{sdtr}=d_s\times\sum_{t\in T}\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, r\in R \tag{10}$$

$$\sum_{s\in S}\delta_{csdt}\leq 1, \quad \forall c\in C, d\in D, t\in T \tag{11}$$

$$\sum_{s\in S}\beta_{nsdt}\leq 1, \quad \forall n\in N, d\in D, t\in T \tag{12}$$

$$\sum_{s\in S}\lambda_{asdt}\leq 1, \quad \forall a\in A, d\in D, t\in T \tag{13}$$

$$\sum_{c\in C_s}\delta_{csdt}=\sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{14}$$

$$\sum_{a\in A}\lambda_{asdt}=\sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{15}$$

$$\sum_{n\in N}\beta_{nsdt}=nn\sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{16}$$

$$\sum_{d\in D}\sum_{t\in T}\lambda_{asdt}=d_s\sum_{d\in D}\sum_{t\in T}\lambda^{start}_{asdt}, \quad \forall s\in S, a\in A \tag{17}$$

$$\sum_{d\in D}\sum_{t\in T}\beta_{nsdt}=d_s\sum_{d\in D}\sum_{t\in T}\beta^{start}_{nsdt}, \quad \forall s\in S, n\in N \tag{18}$$

$$\sum_{a\in A}\lambda^{start}_{asdt}=\sum_{r\in R}\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{19}$$

$$\sum_{n\in N}\beta^{start}_{nsdt}=nn\sum_{r\in R}\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{20}$$

$$\sum_{s\in S}\sum_{r\in R}\alpha_{sdtr}\leq\mid R\mid, \quad \forall d\in D, t\in T \tag{21}$$

$$\sum_{s\in S}\sum_{r\in R}\alpha_{sdtr}\leq\frac{\mid N\mid}{nn}, \quad \forall d\in D, t\in T \tag{22}$$

$$\sum_{s\in S}\sum_{r\in R}\alpha_{sdtr}\leq\mid A\mid, \quad \forall d\in D, t\in T \tag{23}$$

$$\sum_{s\in S_b}\sum_{t\in T}\sum_{r\in R}\alpha^{start}_{sdtr}\leq ba_b, \quad \forall d\in D \tag{24}$$

$$\alpha_{sdtr}, \alpha^{start}_{sdtr}, \lambda_{asdt}, \lambda^{start}_{asdt}, \beta_{nsdt}, \beta^{start}_{nsdt}, \delta_{csdt}\in\{0,1\}, \forall s\in S, d\in D, t\in T, r\in R, a\in A, n\in N, c\in C \tag{25}$$

The multiple objectives displayed in (1), (2) and (3) are all maximized. In (1) the number of surgeries scheduled is maximized and in (2) the profit from those surgeries is also maximized. The objective function in (3) balances the surgeon's preferences and the MSS compliance. The surgeon's preferences are measured according to what they ask for in the surgical proposal and what's given to them in the final schedule. The day and time for the surgery, anesthesiologist and nurses requested by the surgeon are included. The MSS compliance can be translated into the difference between the MSS and the final OR schedule. The balance between these two aspects is regulated by the weights k_1 and k_2. If one of the weights is zero, the model is considered rigid and by introducing non-zero weights for both objectives, the model's flexibility increases.

Constraints (4) ensure that all surgeries in the set are scheduled at most once. Constraints (5) ensure that surgeries can't be scheduled in a closed room and, simultaneously, since for each open room, the parameter σ is 1, no more than 1 patient/surgery is allowed to be scheduled, for any day and timeslot. Constraints (6) make sure that, if a surgery is scheduled to start in a timeslot, room and day, the OR time is allocated for that surgery in that day, room and timeslot, connecting the starting and occupation variables. Constraints (7) ensure that the surgeries are only scheduled for the rooms in which the correspondent specialty can be scheduled, due to the fixed material (type of room).

It is still necessary to make sure that a surgery doesn't start in a timeslot that doesn't have enough following ones to let the surgery be completed. With that in mind, constraints (8) deal with this, not allowing the start of each surgery from a certain timeslot on, specifically from the $| T |$-d_s+1 timeslot. Moreover, if a surgery starts in timeslot t of the day and has an expected duration of d_s timeslots, it means it occupies the room until timeslot $t_1 = t + d_s - 1$. Therefore, constraints (9) translate this relation and assure that the surgery starting in a timeslot, room and day is scheduled at least for the number of timeslots correspondent to its duration. Constraints (10) make sure that for each surgery/patient, the OR time allocated is equal to the surgery duration estimate.

Constraints (11), (12) and (13) assure that each surgeon, nurse and anesthesiologist respectively, participate at most in one surgery at any point in time. Constraints (14) ensure that for each point in time of each surgery, the OR schedule corresponds to the responsible surgeon's schedule. These constraints link the surgeries to their correspondent surgeon. The same has to be verified for the anesthesiologists and nurses which is represented in constraints (15) and (16) respectively. Similarly to constraints (10), constraints (17) and (18) ensure the anesthesiologists and nursing staff allocated OR time, respectively, is exactly the surgery duration. The constraints (19) ensure that if a surgery starts in a day and timeslot, the team of nurses also start that surgery in that day and timeslot. The same happens for anesthesiologists, which is represented in constraints (20). Constraints (21) make sure that at any point in time the number of surgeries happening doesn't exceed the number of functioning operating rooms in the surgical service. The same is assured by constraints (22) and (23) for the nurses and anesthesiologists, respectively, so that at any point in time, the number of surgeries being performed doesn't exceed the team capacity. The downstream unit capacity can't be exceeded as well, which is ensured by constraints (24), similar to what is done in constraints (21).

5. Results

The model is implemented in *Java*, through the *Eclipse IDE* (Integrated Development Environment). *Eclipse* cases the optimizer *CPLEX* to solve the optimization problem, by importing the *Java API* of *CPLEX*. This way, the *CPLEX* libraries are added to *Eclipse*. All the numerical experiments are performed in an Intel(R) Core(TM) i5-5200U, with a 2.20GHz CPU and 4GB RAM memory, running the Windows 10 Home.

The model is firstly technically validated using two toy instances, one with 30 surgeries to schedule, and the second one with 58. With both toy instances, a feasible solution is reached. The total running time is higher, for the second toy instance, which may be due to its higher number of surgeries to schedule. The computational results for both toy instances are detailed in **Table 2**, including results with different k_1 and k_2 weights. Concerning each objective, the number of surgeries is maximized in every test, since the value for that objective corresponds to the number of surgeries in the set S of the respective instance. The same happens for the profit maximization, since the value for that objective is equal to the sum of all the profit values for all surgeries in the set S of the instance, in every test.

Firstly, it is important to mention that, in the second toy instance, for the analysis in which the values should be $k_1 = 0$ and $k_2 = 1$, the values utilized are $k_1 = 0.05$ and $k_2 = 0.95$. This is due to the limited CPU capacity of the machine running the tests. The values used also allow the analysis of the weight variation, since for $k_1 = 0.05$, the surgeon's preferences must also be highly neglected and, for a $k_2 = 0.95$, the MSS is expected to be significantly prioritized. Within the first toy instance, the running time for the weight values $k_1 = 0$ and $k_2 = 1$ is significantly higher than the other two values. This might indicate a higher complexity in the model when trying to achieve only the MSS compliance goal. Although the gap achieved is not zero for almost all the tests, the value is considered optimal. The only exception is for the second toy instance, and weight values $k_1 = 0.05$ and $k_2 = 0.95$, for which a null gap value is achieved.

For both toy instances, it is verified that the model follows all imposed constraints, never include overlapped surgeries, happening at the same time and room and only schedule each surgery once, in open rooms. Each surgery is scheduled entirely in one day and room in both cases, and maximizes all objectives. For equal weight values, a balance is clearly reaches between following the MSS and the surgeon's requests.

Table 2: Computational results for the two Toy Instances

	Weights		Toy Instances	
	k_1	k_2	*First*	*Second*
Number of Variables	-		199 678	387 189
Number of Constraints	-		42 732	81 198
Running Time (sec.)	*0.5*	*0.5*	20.47	843.5
	1	*0*	34.83	5 285.78
	0	*1*	790.7	6 693.03(*)
Gap (%)	*0.5*	*0.5*	0.01	0.01
	1	*0*	0.01	0.01
	0	*1*	0.01	0.00(*)
Best Bound	*0.5*	*0.5*	44 286.01	83 145.36
	1	*0*	44 517.88	83 563.91
	0	*1*	44 107.55	82 869.36(*)
Objective Value	*0.5*	*0.5*	44279.55	83 138.96
	1	*0*	44513.55	83 556.46
	0	*1*	44104.55	82 868.76(*)

(*)For the second toy instance the weight values used are $k_1 = 0.05$ and $k_2 = 0.95$.

Overall, when the weight k_2 is 1 and k_1 is 0, the model maximizes the MSS compliance, since it follows almost entirely the MSS. Also, when the weights have these values, the surgeon's request is, without a doubt, neglected. This can be inferred since, even in cases where the surgeon asks for an hour concordant with the MSS, the surgery is scheduled for any time that follows the MSS, but not for that specific time the surgeon wants. Still, for both nursing teams and anesthesiologists, the model ignores the surgeon's request again, assigning, in most of the times, any random available team to each surgery. On the other hand, when the values are switched (k_1=1 and k_2=0), almost all the surgeries are scheduled according to the surgeon's preferences, some of them matching the MSS because the request is compatible with it. Both nurses and anesthesiologists preferences are also followed. This way, it can be considered the inclusion of the preferences is being maximized. Finally, when the weights are equal to each other, being both 0.5, the final schedule presents a balance of the third objective.

5.1. Results with real instance

A real instance is built, using data from an entire week, collected from the hospital. For this instance, the surgical proposals that correspond to the surgeries scheduled, in an entire week, are gathered. The information from these proposals is used, to build the parameters needed for the model. In this instance, a total of 46 surgeries are in the list to be scheduled. When collecting the information, the proposals are often poorly filled, leaving omitted crucial aspects for the scheduling process. Additionally, some proposals are not found, or not available for the study. Furthermore, none of the surgeons fill out the part where they have to specify the surgical team. Thus, the surgeon's preferences will only include the day and hour for which the surgery is requested. Two nurses and one anesthesiologist are assigned to each surgery, however, the team will not try to match the surgeon's request.

The profit margin for each procedure is not available, therefore, is not presented nor included in the objectives. However, for this number of surgeries to schedule, the two first objectives are redundant. Since all the surgeries fit in the schedule, both profit and number of surgeries scheduled are maximized. The fact that the profit is not included in this instance becomes irrelevant, because, if available, the profit maximization only causes all the surgeries to be scheduled, which is assured by the objective that maximizes the number of surgeries scheduled. In **Table 3** the computational results for the real instance are presented. All surgeries are scheduled in all tests, leading to a maximization of the number of surgeries scheduled objective.

For equal weight values, a clear balance is achieved between following the MSS and the surgeon's request, which hasn't been reached by the hospital. The resulting schedule (**Figure 1**) for those weights is consequently the most attractive to the stakeholders. Concerning the surgeon's schedule, each assigned surgeon matches the respective surgery's responsible surgeon. Still, the weight variation analysis is performed, to assess if a more suitable schedule can be achieved.

The surgeon's request is prioritized for the weight values k_1=1 and k_2=0. The cases in which the surgery is scheduled respecting both MSS and request may be coincidental, as the request matches the MSS. For the surgeries without a request available, some are scheduled respecting the MSS, but most of them are not. This indicates the MSS is being neglected, since all these surgeries respect the MSS for a not null value of the weight k_2. Situations of surgeries only taking into consideration the request appear, comparing to the previous analysis in which these are absent. On the other hand, in the result for the weight values $k_1 = 0$ and $k_2 = 1$, the surgeon's requests are obviously ignored. The value of the objective part concerning the surgeon's request is significantly lower (5) than the one concerning the MSS (152). That small value for the surgeon's preferences results from certain timeslots matching the surgeon's preferences. However, these are not significant to consider that an entire surgery is scheduled according to the surgeon's request. Therefore, all surgeries are considered to be scheduled only respecting the MSS.

Table 3: Computational results for the Hospital Instance

	Weights k_1	Weights k_2	Hospital Instance
Number of Variables	-		313 547
Number of Constraints	-		56 318
Running Time (sec.)	*0.5*	*0.5*	3 155.77
	1	*0*	4 556.88
	0	*1*	4 153.52
Gap (%)	*0.5*	*0.5*	0.00
	1	*0*	0.00
	0	*1*	0.00
Best Bound	*0.5*	*0.5*	162.00
	1	*0*	160.00
	0	*1*	198.00
Objective Value	*0.5*	*0.5*	162.0
	1	*0*	160.0
	0	*1*	198.0

The schedule built by the hospital, for the same week, can be compared with the results obtained, mainly with **Figure 1**. It can't be concluded that one schedule is entirely better than the other. The instance available, corresponds to a week with low production, which means, the number of surgeries in this week is less than the average number throughout the year. For that reason, one aspect in which the hospital schedule surpasses the model's results, is the absence of surgeries scheduled over the weekend. Another aspect for which the hospital schedule can be considered better, is for the surgeries with unavailable requests. Specifically, the ones with the same responsible surgeon, in the hospital schedule, are all sequential and compatible with the MSS. However, the hospital had the requests available when building the schedule, so this comparison is not quite valid. For the remaining surgeries, most of them don't match the surgical proposal in the hospital schedule, which confirms the existing difficulty in integrating the MSS and the surgeon's preferences. Moreover, in situations for which the surgeon's preferences match the MSS, both should be attended, since this is the ideal situation. This is verified in the model's resulting schedule, however, not in the hospital schedule, confirming the model outperforms the current scheduling strategy when achieving this goal.

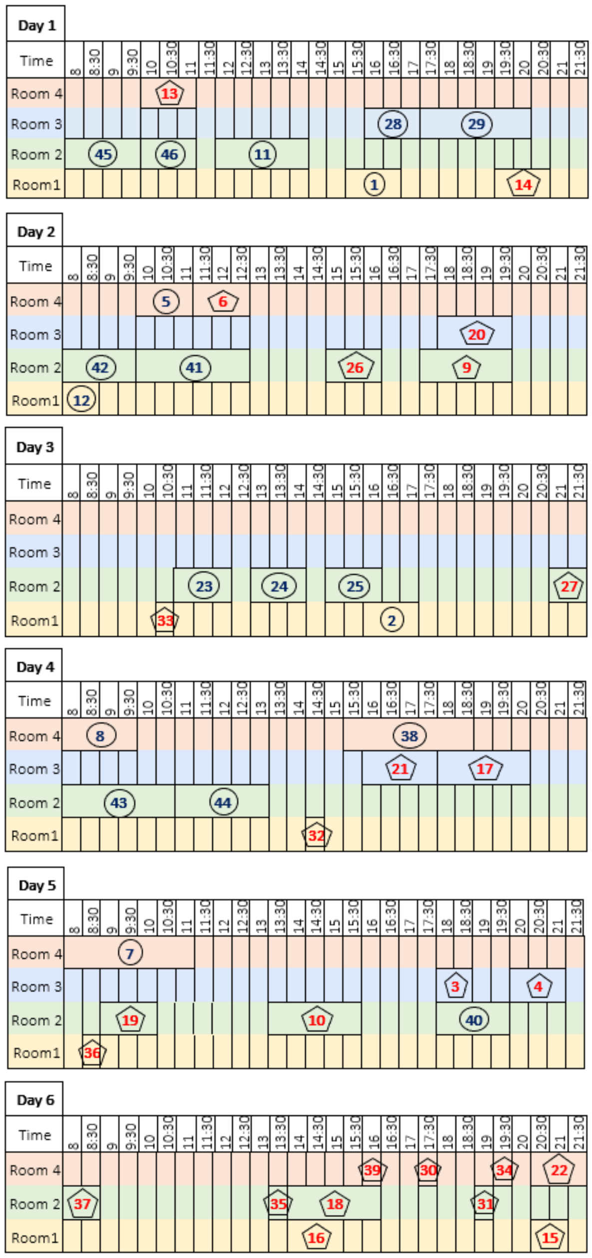

Figure 1: Final OR Schedule using the Hospital Instance, with weight values for third objective of: $k_1 = k_2 = 0.5$. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

5.2. Hospital Validation

To gather the main stakeholder's feedback, an interview with the chief of surgery is conducted, which allows consequent managerial insights. In the meeting, first, the mathematical model is explained, and an introduction is performed, to the concepts of objective function, constraints and weights. All the adjustments done when building the model, comparing to the real situation, are described and justified.

The solutions are well received by the chief of surgery, who understands the potential use of this model, however there are several setbacks needed to be solved, to allow the use of these models in their full potential. The main concern indicated by the chief of surgery, is the lack of properly filled surgical proposals, which also limits the application of the mathematical model to real data. An solution, proposed by the stakeholder, is an electronic surgical proposal, with mandatory fields and restrictions to the requests.

Furthermore, the chief of surgery considers that the OR is not as profitable as it could be, and the main cause is the access to the OR, by external surgeons. The hospital's administration strategy is to accept every external surgeon that requests OR time, to attract more patients to the hospital. This causes an unreasonable number of surgical teams, and a consequent excessive heterogeneity in the team. Having an homogeneous team of surgeons, i.e., an entire team of internal surgeons, who work every day in the hospital, is preferable. With less surgeons, the probability of overlapped surgical requests decreases, easing the maximization of the surgeon's preferences and also, the MSS acceptance, and will to follow it, becomes more likely. The team work needed to have an efficient OR is also enhanced, if all team members work together daily. Finally, external surgeons usually don't have the hospital's best interest in mind, as much as an internal surgeon does.

The chief of surgery highlights the concern with the unsuitable use of the hospital infrastructures. Aiming again at attracting patients, the administration includes Ophthalmology in the OR, for which the surgeries are ambulatory. An ambulatory unit, which doesn't exist in the hospital, has a completely different structure. Procedures are much faster, having a flow of patients entering and exiting the ambulatory OR much higher than in a regular OR. These surgeries are supposed to be separated from inpatients, and having them being performed in a regular OR compromises its workflow. The chief of surgery expresses the urgent need for the hospital to be managed considering its facilities and infrastructures, instead of being managed in spite of these. By trying to include types of services that are not suitable for the hospital, instead of potentiate the hospital's growth, the overall efficiency decreases, the optimization becomes more difficult, decreasing profit and not providing better care.

Considering the profit aspect mentioned by the stakeholder, ambulatory surgeries are an example of this concern. It is preferable, for the OR, to have one inpatient surgery scheduled, occupying a big time block, than have an entire shift filled with multiple ambulatory surgeries, because the inpatient surgery is associated with a higher profit margin for the hospital. To conclude the conversation, the chief of surgery refers the three main foundations of an OR, which are the people, as in the staff members, the material and the internal teams. All these three aspects have to be well-managed in order to have an efficient OR.

Moreover, with some changes to the schedule from **Figure 1**, an ideal schedule can be achieved. Additional suggestions are also made by the stakeholder, such as impose that the same type of surgeries should be scheduled sequentially, which implies characterize each surgery according to the type of procedure and therefore, gathering additional information.

6. Conclusions

In hospitals, surgical services are a main source of income and costs, so optimizing its operations is essential financially. The stakeholders easily identify the main sources of issues in the department, and the scheduling is chosen as the problem to solve. The main novel feature in this study is the balance between following the tactical decision made by the hospital and the surgeon's preferences.

An ILP model is developed, to optimize the OR scheduling of elective surgeries. The main objective identified with the stakeholders, is the balance between respecting the MSS implemented in the service and the surgeon's preferences. The human resources, room and downstream unit capacities and types of rooms, according to the existent material that can't be transported, are included as constraints in the model. The model's performance is satisfactory, presenting, for all numerical tests, acceptable running times (all bellow one hour) and, with a real instance, an optimal gap value is always reached. The model reaches the balance intended, in way the hospital hasn't been able to do. According to the chief of surgery, the results highlight the main issues in the OR, mainly the absence of an electronic surgical proposal.

The main setback associated with this work is the limited access to real data. The fact that all surgeon's don't entirely fill the surgical proposal, also influences the results. The way the downstream unit capacity is considered is not accurate, as a schedule for this unit should be done separately and considered. Additionally, uncertainty is inevitably associated with the surgery duration and LOS, which can be furthered added. The non-elective cases appearances can also be added as a stochastic feature in the future. Finally, equal procedures should be scheduled sequentially, with the proper information gathered, which can be added to the model as well.

The model has the potential to add value if inserted in the case study OR management. By following some of these suggestions in the future, the model's value increases. Finally, with the changes necessary, by the hospital's administration, the model can be implemented and optimize the OR operations.

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