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

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Preface

The work presented in this thesis was performed at the Centre for Management Studies of Instituto Superior Técnico (CEG-IST) (Lisbon, Portugal), during the period March-October 2019, under the supervision of Prof. Inês Marques, within the scope of project PTDC/EGE OGE/30442/2017, Lisboa-01.0145-Feder-30442.

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Acknowledgments

First of all, I would like to thank my supervisor, Professor Inês Marques, who guided me through this work, always pushing me to work hard and give my best in everything I do. I would also like to thank Dr. Rodrigo Oliveira, the chief of the surgical department where the study took place, for his availability and support, and to the hospital for allowing me to perform my research in a real hospital context. Finally, I want to thank my family and friends, for the constant presence and support in my life, especially throughout these last 5 years, and for always believing in me.

Resumo

O bloco operatório representa uma porção significativa dos custos e receitas totais de um hospital. Uma gestão eficiente, facilmente se reflete nos resultados financeiros do hospital e potencia a qualidade dos serviços prestados no mesmo. O agendamento constitui uma atividade central no bloco operatório, já que determina diretamente o funcionamento diário do serviço. No caso do hospital em estudo, a implementação de uma nova estratégia de agendamento é indicada como urgente pelos membros da equipa do serviço. Neste trabalho, é desenvolvido um modelo de programação linear inteira, com o intuito de otimizar o agendamento de cirurgias eletivas. Os objetivos incluem maximizar o número de cirurgias agendadas, o lucro total e o equilíbrio entre seguir o *Master Surgery Schedule* (*MSS*) do hospital e os pedidos dos cirurgiões. A capacidade do serviço em termos de salas e recursos humanos (enfermeiros e anestesistas), tipos de salas e capacidade do serviço pós-operatório são considerados. Este estudo contribui para a literatura através da integração das preferências dos cirurgiões e decisões táticas do hospital. A introdução destas preferências como objetivo e a inclusão de dia e hora para a cirurgia, enfermeiros e anestesistas nestas, constitui uma característica inovadora do estudo. A solução exata obtida utilizando dados reais, integra o *MSS* e as preferências dos cirurgiões com sucesso. Os resultados também evidenciam os atuais problemas a resolver no bloco operatório, que constituem um bloqueio na aplicação do modelo aos dados reais. Os resultados computacionais são satisfatórios, já que o modelo atinge uma solução ótima.

Palavras-chave: Bloco Operatório, Agendamento de Cirurgias, Preferências, *Master Surgery Schedule*, Programação Linear.

Abstract

The Operating Room (OR) represents 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 Master Surgery Schedule (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 constrain the application of the model to real data. The model presents satisfactory computational results, as it provides an optimal solution.

Keywords: Operating Room, Surgery Scheduling, Preferences, Master Surgery Schedule, Linear Programming.

Contents

List of Tables

List of Figures

List of Acronyms

ACO	Ant Colony Optimization
BB	Branch-and-Bound
BLP	Binary Linear Programming
BRKGA	Biased Random-Key Genetic Algorithm
CCP	Chance-Constrained Programming
CCSP	Chance-Constrained Stochastic Programming
CGBH	Column-Generation Based Heuristic
CP	Constraint Programming
DES	Discrete Event Simulation
GRASP	Greedy Randomized Adaptive Search Procedure
HGA	Hybrid Genetic Algorithm
ICU	Intensive Care Unit
ILP	Integer Linear Programming
ILS	Iterative Local Search
KP	Knapsack Programming
LOS	Length of Stay
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MIP	Mixed Integer Programming
MSS	Master Surgery Schedule
OR	Operating Room
SA	Simulated Annealing
SAA	Sample Average Approximation
SNS	Serviço Nacional de Saúde
SP	Stochastic Programming
SPIP	Set-Partitioning Integer Programming
VNS	Variable Neighborhood Search

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Chapter 1

Introduction

To introduce this thesis work, the motivations are described as well as the main contributions to the literature, in **Sections 1.1** and **1.2**, respectively. To complete this introductory chapter, the thesis structure is detailed in **Section 1.3**.

1.1 Motivation

A surgical service has a significant impact in the hospital's management. May et al. [1] consider that a surgical center is 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. Lamiri et al. [2] estimate that an OR can be responsible for approximately 40% of a hospital's total revenue. Therefore, it is clear 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 extensively addressed in the literature, to attempt at optimizing these issues. On the other hand, although extensively studied, OR planning and scheduling are problems that need continuous improvement. Mainly because when optimizing a health activity, these 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 changes, that can be implemented in other types of sectors, 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. Therefore, when introducing a new strategy, the staff has to be considered, since their experience provides a significant contribution to the proper care of the patients.

This work aims at optimizing the OR scheduling of elective surgeries, in the case study hospital, by developing a new 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). In this objective, are translated the hospital's interests and the staff satisfaction, both major aspects to consider when optimizing the OR scheduling. The number of surgeries scheduled and the total profit associated with these surgeries are also maximized. The main constraints to consider in the case study OR are the human resources, including nurses and anesthesiologists, and room capacity, as the number of open rooms constraints the schedule. Rooms with specific material resources, that can not be transported, constraint the schedule of certain surgical specialties. This is currently an issue in the hospital, because there are situations of surgeries scheduled in rooms without the material necessary for the procedure. The downstream unit capacity also represents a constraint in the OR scheduling, since a patient can not have a surgery scheduled, if no bed is available for the postoperative phase.

Currently, in the case study hospital, the OR schedule is built by a specific worker, and reviewed by a group of members of the department administration. This worker has to consider all the aspects mentioned as constraints, and still deal with setbacks like incomplete and unreadable surgical proposals, or even the absence of these, when surgeons try different paths to have their surgeries scheduled. The MSS is significantly considered when building this schedule, and the surgeon's preferences considerably neglected. This may lead to unsatisfied workers, which is never a good indicator for a department. Consequently, these workers lose their interest in providing requests compatible with the MSS. Integrating the surgeon's request with the MSS, to obtain the final schedule, can represent a solution for a optimal schedule.

The implementation of a scheduling strategy only requires the worker, currently responsible for scheduling, to validate the final schedule. It can also avoid situations of postponements or cancellations due to bed unavailability, or of surgeries scheduled in rooms without the material needed. A scheduling tool, that optimizes the weekly OR schedule, is needed in the hospital, to achieve the goals set and improve the efficiency in the OR.

1.2 Contributions

The relevant OR scheduling studies can be mainly divided according to the decision levels. The tactical and operational levels are considered in this study. Strategic level decisions in the OR are not included in the scope of this work. 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, assigning a team and a date to each surgery selected. As waiting list, from which the surgeries are selected to be scheduled, are used all the surgical proposals for a whole week. Since emergency surgeries are not taken into consideration, and operational decisions are made, this study falls in the category of *Elective Surgery Scheduling*. The model developed is a deterministic ILP mathematical model, representing an exact solution approach to obtain the final OR weekly schedule.

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 surgeon's preferences similarly to this study. First, most studies that consider the surgeon's preferences, only do that in terms of staff affinity, and these are included in the constraints [3, 4]. 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 [5]. The surgeon's preferences are included in the objectives by Penn et al. [6], 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, the surgeon's preferences are not only considered as an objective, but also are considered in terms of day and hour to schedule each surgery, nursing team to assist and anesthesiologist preferred. In addition, the balance between meeting the tactical decisions of the hospital, and the surgeon's request is also a contribution to the literature.

It can also be considered that it is not found in the literature, an operational study including, simultaneously, types of rooms (the type is related with the appropriate specialty to be scheduled in the room, according to the material needed), downstream resources, human resources, surgeon's preferences and tactical decisions, namely the MSS.

1.3 Thesis Outline

Firstly, in this introductory chapter, the motivation to pursue this work and its main contributions are described. In the next chapter, the case study is addressed and contextualized, to conclude the focus of the study. The hospital's current situation and management strategies are detailed and the sources of possible issues in the OR inferred. Afterwards, in the third chapter, the existent relevant literature is presented, concerning mainly tactical and operational level OR scheduling studies. The deterministic mathematical model developed is presented in the fourth chapter, including the assumptions previously made, objectives and constraints. A technical model validation is specified in the fifth chapter. The toy instances used for this validation are firstly described. Then, the computational results, using the instances described, are presented and analyzed.

The sixth chapter presents the results using real data. First, an instance built using data collected from the hospital is described. Then, the results of applying the model to that instance are discussed. In addition, a model validation, from the hospital's point of view is assessed. With that purpose, an interview is conducted with one of the main stakeholders, the chief of surgery, and the work carried out is overviewed. Stakeholder's feedback and comparison with the current OR situation are then detailed, and some managerial insights are inferred.

This thesis is concluded, in the seventh chapter, with the description of the main achievements associated with this work. In addition, limitations in the model developed are identified and future work suggested.

Chapter 2

Contextualization

The study of the OR operations and their efficiency is a relevant area, since the surgical service represents the highest source of income in most hospitals. It is also the service with the highest associated costs. Thus, optimizing the overall process, easily increases the hospital's income and reduces costs, therefore increasing profit. Furthermore, the materials utilized are usually the most costly, the staff is highly specialized and the type of procedures are usually the most sensitive, since they can cause the most damage to the patient. Therefore, each operation related with the surgical service has to be properly handled as it can both damage or benefit significantly the hospital's management and the patient's health.

In this chapter, is presented a brief description of the hospital's context and a more detailed one about the OR system at the hospital (**Section 2.1**). The operations are explained and the sources of the lack of efficiency identified for further analysis and modeling. Finally, in **Section 2.2**, conclusions are inferred concerning the whole chapter.

With more than 50 years of existence, the case study hospital represents a private health institution that provides healthcare services, within 35 health specialties. Its main focus is providing high quality health services to improve the patient's health status and guaranteeing the patients well-being, at all times. Throughout its history, this institution has always tried to provide the best healthcare to its patients, using cutting-edge technology and modern techniques [7]. Currently its management is held, in 45%, by a public holding company, and the remaining, by a private management society created specifically to manage the hospital [8].

To guarantee the best healthcare provided to the patients, the hospital holds agreements with several health insurance companies and private and public health subsystems. This way, all the population benefiting from these insurances or subsystems is allowed to receive high quality services given in this institution. Additionally, this hospital partnered with the health ministry, providing care together with *Serviço Nacional de Saúde* (SNS) and integrating the list of the national network of healthcare providers.

2.1 OR Management

Within the hospital, the surgical service accounts for the highest source of income, as well as the highest associated costs. This can be easily explained by the highly specialized human and material resources that are daily utilized in this type of service. Therefore, optimizing the processes in this service should contribute with major impact for the hospital's financial state. To allow improvement interventions, the OR management must be well-known. With that in mind, the working ways of the service and the perioperative processes are described in this section.

This surgical service is located across three floors of the hospital, two of them hold together the 8 existing operating rooms, and in all three of the floors there are bedrooms for inpatients. One of those operating rooms corresponds to what it is called an hybrid room, i.e., the room in which all the hemodynamic procedures are performed, but that also allows, at any point of the procedure, to open up the patient and proceed to a surgery. This is possible, since all the equipment, for both types of procedure, is available in that specific room. The whole surgical service operates from 8 a.m. until 10 p.m., from Monday to Saturday.

2.1.1 Indicators

In 2018, the case study OR registered 6 585 surgical procedures, which represents a 1.3% increase in this number, when compared with 2017 [9].

In terms of human resources, specifically surgeons, it was lastly counted 186 surgical teams. This number includes all the surgeons from outside the hospital's team, that go there only to perform their surgeries. It is clear that all these teams can not be regular in this OR, since this number is extremely high, being inconsistent with the OR's utilization. Furthermore, no record is kept of how many of these teams belong to those external surgeons, that only go to the hospital when they have a surgery scheduled there. 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 a well-functioning and efficient service. Although there is a total of 8 operating rooms, currently, only 5 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.

Concerning the utilization rate, this concept is complicated, since a high utilization does not 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 service. Moreover, the calculation of this value has significant errors associated, as it is obtained only with the number of existent rooms and the hours they are being utilized, which is not totally accurate. The OR may have rooms available and patients to operate, but not a surgical team ready to use the room, and this has to be taken into consideration when talking about the OR utilization. This rate can be analyzed, but only if all these aspects are considered. Currently, the utilization rate is estimated to be around 40%, and this low value can be explained by multiple different reasons, which are not detailed. That is why a justification should always be attached to the resulting value. It is also verified that in an usual daily OR schedule, around 7 p.m., the OR utilization decreases drastically, even though there are still three useful OR hours.

Additionally, considering the number of operating rooms in this service and its utilization, the high number of surgical teams can be further discussed. This number is this high, probably because the external teams are excessive and not always the same. Still concerning the external surgeons, when they schedule a surgery, the hospital must provide the remaining human resources needed in a surgical team, apart from the surgeons and, in some cases, anesthesiologists. This can cause an even higher human resource constraint, as the nursing staff is already short when working only for the internal surgical teams.

2.1.2 Scheduling

For non-elective patients, a situation is considered emergent when the patient has to be treated in the moment. On the other hand, an urgent one occurs if it is possible for the patient to wait up to 24 hours to receive the proper treatment, without risking the patient's life or possibility of recovery.

When dealing with non-elective surgeries, the strategies implemented aim at its agile introduction in the daily schedule. When a patient has to undergo surgery in a situation of emergency or urgency and both operating room and surgical team are available, no changes are made to that daily schedule. But when there are no resources or place available, the situation has to be assessed. Firstly, the level of urgency is analyzed and, if it can wait until one of the procedures end, the surgery is scheduled after the first-ending procedure. In this situation, the rest of the daily plan is delayed according to the time the procedure takes. On the other hand, when the situation is classified as emergent and it can not wait until the next-ending surgery, one of the currently undergoing procedures has to be interrupted so that the emergent situation is handled.

Previously, the hospital had an operating room and a anesthesiologist dedicated entirely to non-elective procedures. This means that an urgent or emergent patient would always have a room and a anesthesiologist ready to treat him/her. However, this strategy has shown to not be the most efficient in this hospital. This would mean that while there were no emergencies coming, both the room and the physician were being wasted, translating in a financial loss by having unused resources. In fact, it was verified that these resources were not being used very often and therefore were being wasted overall. Moreover, even with a room and an anesthesiologist constantly available, surgeons and nurses were also necessary and could be performing some other procedure. In this case, that procedure had to be stopped, showing that even with dedicated resources, the daily schedule would be affected.

The most common situations in emergency departments, that require a surgical procedure, consists in injuries caused by accidents, i.e., trauma surgeries. These are taken to trauma centers, which are usually public hospitals. Thus, the low volume of emergency surgeries appearing is easily explained. Applying a strategy like the one previously mentioned is not justified, and is not an efficient decision, management wise. The current way to handle the few cases that appear is verified to work better, not wasting so many resources. It is also observed that most of the times, when the surgeons delay their daily schedule, they end up treating all the patients in that same day anyway.

On the other hand, the elective patients are the typical ones in the case study OR and, to schedule a surgery, certain steps have to be respected. To begin, a surgical proposal has to be submitted by the surgeon, after the appointment with the patient, where the date and hour is required, as well as the material and team necessary.

Currently, the proposal strategy is being changed and the main difference comparing with the previous process is in terms of the permanent OR material. This material, is the one that is placed in a certain room of the service and all the surgeries which require it, must be allocated to that specific room. This is done due to the fact that the transportation of this material represents a high probability of damaging it. This type of material usually does not have to be purchased or ordered from the central warehouse for that procedure, so it would not be present in the surgical proposal before. Consequently, if the person booking the room does not know or does not pay attention to the type of procedure in question, it can be scheduled in a room without the material needed.

Instead, in the new proposal structure, this material has to be detailed so that the surgery is certainly scheduled in the room where the material is placed. This proposal is intended to be the only way a surgery can be scheduled and has to be submitted with a certain time left to the surgery date. The department administration approves and seals the weekly schedule by the end of the previous week, usually with a Friday meeting. In that meeting, a pre-schedule is already available and the downstream resources and surgical teams' availability are revised and changes are made, if necessary. When the schedule for the entire week is compatible, it is approved and released.

The surgical proposal model includes, first, elements like the date and time to schedule the surgery. Then, the surgical proposal itself has to be described, with relevant aspects about the patients and their health insurance. The next elements in the proposal are the surgery duration estimate, expected patient arrival time, and distinction between inpatients and ambulatory surgery cases. For inpatients, details such as expected Length of Stay (LOS), in days, and the type of postoperative care needed are also included. The preoperative indications are described in the following section of the proposal, when necessary, and each member of the surgical team is requested. Here, the surgeon, assistant(s), anesthesiologist and scrub nurses are all specified. The proposal is only complete with the description of the surgical plan, important codes and material needed. In the end, there is a small space for possible observations.

Table 2.1: Weekly Master Surgery Schedule, from Monday to Friday

	OR2/3	OR4	OR5	OR6
Morning shift (8 a.m. - 4 p.m.)	Cardiothoracic Surgery and Ophthalmology	Orthopaedic Surgery (internal surgeons)	Vascular Surgery	General Surgery
Afternoon shift (4 p.m. - 10 p.m.)	Angiographic and Vascular Access Procedures	Orthopaedic Surgery (external surgeons)	Other Specialties	Urology

An important aspect, when scheduling a surgery, is the procedure duration estimate, which is commonly included by the surgeon in the surgical proposal. In the current strategy, the surgeon can estimate the time the surgery will take or, alternatively, use the hospital's estimates, defined for all the procedures carried out in the service. Using the hospital's estimates means that, for the same procedure, the estimate is the same independently of the surgeon performing it. This estimate is based on historical values, which may represent a more accurate strategy to estimate that time.

To organize the weekly schedule, time blocks are assigned to the surgical specialties, restricting each specialty schedule. The ones that correspond to a higher number of patients, representing bigger sources of income, are General Surgery, Cardiothoracic Surgery, Vascular Surgery, Urology, Orthopaedic Surgery and Ophthalmic Surgery. Therefore, these have a larger time block assigned, comparing to the remaining. Currently, a new block scheduling strategy is being implemented and the OR time assignment, on a weekly basis, meaning, the MSS, from Monday to Friday, is represented in **Table 2.1**.

For Orthopaedic Surgery, the surgical teams that work permanently in the hospital, referred to as internal surgeons, have the morning shift assigned to them. On the other hand, the teams that go to the hospital only to perform the procedure, called external surgeons, have the afternoon shift, of the same room, allocated to their surgeries. For the remaining specialties, this is not done due to the lower flow of external teams compared to Orthopedics. Instead, the external surgeons' surgeries are scheduled after the internal ones, having to settle with the available time blocks. When ”Other Specialties” is mentioned, it concerns the remaining surgical specialties for which the number of patients is not as significant as the ones mentioned before. This group of other specialties refers to Gynecology, Otolaryngology, Neurological Surgery, Oral and Maxillofacial Surgery and Plastic Surgery. Any surgery, from an outside surgical team, can also be scheduled in this time block.

Concerning weekends, only Saturday is considered and the only time blocks assigned are the afternoon shift, in OR2/3, for Vascular Access Procedures, and the morning shift, in OR6, for Gynecology and Otolaryngology. Since the scheduled patients are majorly during the week, the remaining Saturday schedule is empty and available for any type of procedure or surgical team. Also, apart from the two assigned rooms in the MSS, only one room is open on the weekends.

2.1.3 Patient Pathway and Staff

The elective patient's flow through the perioperative processes is not mapped nor officially defined, but it is possible to draw a typical pathway, from the moment the patient enters the service, until he/she goes to the recovery room.

First, the patient is admitted and assigned to a room, in one of the floors, not necessarily a surgical floor nor the same floor as the surgery will occur. When the operating room is available, preferably at the surgery's scheduled time, the patient is transported to the outside of the operating room, by a specific worker whose job is the transportation. Then, usually the patient is transferred to the inside of the respective room and the anesthesia is given. Not often, and only in situations of local anesthesia, patients can be given the anesthesia outside the operating room, where they are waiting to enter, while the room is being cleaned, to save time. After the patient undergoes surgery, and as soon as the procedure reaches its end, the patient is transported to the postoperative unit, to a recovery room. When the patient recovers from the anesthesia, they return to the bedroom, where the follow up is done and the patient remains, until ready to leave the hospital.

Having a specific worker to perform the transportation, represents a positive aspect, since no other resource, possibly more specialized, such as a nurse, is being used for a job for which no high qualifications are necessary. The transportation to the recovery room is done by the same transporter.

Concerning the staff, the majority of the surgical teams, including surgeons and anesthesiologists, are not full-time workers of the hospital, only working in the hospital in the hours where their surgeries are scheduled. For each surgeon or surgical team, there is no official agreement or contract that defines the hours in which their surgeries should be scheduled. With time, these hours are defined according to the surgeons' preferences and habits, and can be altered.

2.1.4 Sources of inefficiency

A common aspect in which there is waste, in this type of services, in any hospital, is time. Nevertheless, this does not seem to be a major issue in this surgical service, since the common predefined turnover time and duration estimates are usually respected. These estimates are either based on staff experience or on a list of average times for each procedure, that the service has available. In addition, the majority of the situations in which the estimates do not match the reality, causing delays, the reasons involved are unpredictable, uncontrollable and impossible to predict, such as complications during the procedure.

The only relevant situation found that indicates a waste of time is in the bedroom assignment. The fact that a patient may have its bedroom in the first surgical floor and the assigned operating room in the third one, may represent a source of waste, especially of time. The waste is more evident if there is another patient in the opposite situation (operating room in the first surgical floor and bedroom in third).

In addition, increasing the transportation's distance is not beneficial for the patient, which represents a negative consequence more important than wasting time.

When the cancellation rate is assessed, considering only the situations in which the patient cancels, this value is not considered significant. Since these situations occur very scarcely, the overall service functioning, and its efficiency, are not affected. Concerning non-elective surgeries, they do not represent an issue to the good functioning of the service, as there is not enough case-volume to justify a different strategy than what is currently being done.

The number of surgical teams currently performing surgeries, clearly reflects the uncontrolled number of external surgical teams. Therefore, there is a high variability associated with these outside teams and their presence, which can represent a relevant issue. 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 and their preferable hours started to become usual. In the majority of the cases, these teams are not willing to change their schedule. This causes overlapped preferential schedules, while there are available rooms in other hour within the same day, for example. So basically, there are empty spaces and overlapped surgeries, simultaneously. These issues can also justify the unbalanced number of surgeries throughout the week days and the unused operating rooms after 7p.m.. This is a clear representation of the uneven use of the service capacity, and coherent with the fact that the OR is not used to its full capacity (low utilization rate).

Although the demand is continuously increasing, and the facilities have the capacity to take more daily surgeries, the OR schedule is not full. Therefore, it can be inferred the OR is not being used to its full capacity, leading to the observed low utilization rate. The main reason is the shortage in the staff, mainly a lack of anesthesiologists. The nursing staff deficit mentioned complicates the OR management, as it can be easily understood. Measurements like closing some of the rooms helps smooth this lack of resources.

Despite the new MSS built, scheduling still represents the hardest aspect to work on, mainly when dealing with the external surgical teams. These outside teams have their schedule restricted with this new approach, and may not be satisfied with losing the total freedom to schedule their surgeries. Thus, if the availability and willingness to change from the surgical teams' side is not reached, other strategy has to be adopted. On the other hand, the workers' satisfaction is a major indicator of good care delivery and service efficiency. So, developing a balance between the OR's interests and satisfying the surgeons might be the right way.

Finally, another aspect concerning the external surgeons is relevant. When performing a surgery in this OR, the surgeons are the only human resource that comes from the outside of the hospital, and, rarely, the anesthesiologist. The remaining members needed to perform the procedure, are provided by the hospital. If the hospital alone already faces a shortage in terms of nurses, with these external teams also needing the hospital's nurses, this issue is enhanced.

Furthermore, there is still a lack of compliance concerning the surgical proposal submission. A significant portion of the surgeons, instead of sending the intended proposal to the corresponding office, try to book the surgery through a phone call or in person. The fact that not all surgeries enter the list to be booked in the same way, makes it harder to organize the OR plan and the surgeries that are supposed to be scheduled. Another relevant consequence of having several paths through which the proposal is done, is the absence of downstream resource consideration. Thus, a person can arrive to the hospital to be admitted for the scheduled surgery and not have a bedroom to stay in, therefore being obligated to postpone the surgery. This type of situation is inconvenient for the surgeon and specially for the patient, decreasing their satisfaction, and representing a strong evidence of inefficiency.

Moreover, not only surgeons try to book a surgery through a different path, but also do it in the day before the surgery, for example. Each proposal is supposed to be submitted at least before the meeting of approval for the next week's schedule. By not respecting this time interval, the OR planning becomes much more difficult.

Concluding, in the OR in study, to try to solve, simultaneously, the high number of detected issues, optimizing the surgery scheduling might by the right path. By providing a new scheduling strategy, it is possible to improve, or at least highlight and prove the existence, of issues related with the utilization rate, uneven OR use, external surgeon's scheduling issues, surgical proposals issues and lack of MSS compliance. Additionally, since solving other mentioned issues, such as the deficit in terms of human resources, involves decisions from the administration, these problems are not considered solvable through optimization methods. However, the use of the existent human resources capacity can be optimized with a scheduling optimization technique. Thus, if the staff capacity can not be increased, optimizing the existent one is the best option. Ideally, the staff satisfaction and following the MSS, surgical proposal strategy and other tactical decisions made by the hospital should be combined. This combination must be done in a way that balances the improvement of all these relevant aspects, leading to the OR operations optimization.

2.2 Chapter Conclusions

In this chapter, a contextualization of the case study is presented. Starting with a general view of the hospital, the chapter evolves into a more detailed description of the surgical service. Processes related with the OR management are detailed, concerning the case study, and the main issues are identified. Afterwards, the issues identified and solvable are the ones to focus on, by developing a solving technique to tackle them. Specifically, the elective surgery scheduling is inferred to be the main concern to assess in this work.

In the following chapter, a review of the literature, concerning mainly OR planning and scheduling problems, is performed.

Chapter 3

Literature Review

To develop a solving method for the OR scheduling problem, the existent literature has to be known. Thus, it becomes relevant to describe the methods that have been implemented in surgical services to optimize the scheduling process. With that in mind, a review of the existent literature is executed and taken into consideration.

As concluded in the previous section, the main concern is surgery scheduling. For this matter, an enormous variety of strategies have been developed, to solve the different problems that have been identified. 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.

Concerning the decisions in a tactical level, the problem consists in a *Master Surgical Schedule* (MSS) problem. The MSS uses a fixed "grid", for a fixed amount of time previously defined, called the planning horizon. This "grid" defines which specialty is assigned to which daily OR time blocks. A planning cycle is applied when the MSS is cyclical, consisting in several planning horizons, and in each one a different "grid" is utilized. This way, the OR time blocks assigned to the specialties vary in time, going back to the same in the beginning of each planning cycle. Usually the cycle period is one week, two weeks or one month [6, 10]. It is considered that the timetable should be revised whenever the total amount of OR time changes [11].

Within the operational level, two stages can be considered in the surgical planning and scheduling problem. Firstly, the planning problem has been defined, by Lamiri et al. [2], as deciding the group of elective patients, from the waiting list, that should have their surgeries scheduled, and in which schedule period, having a waiting list and a finite planning horizon. This represents the *Advance Scheduling*, sometimes also called *Surgical Case Assignment Problem*. Whereas the scheduling problem has been described by May et al. [1], as selecting the procedures to be performed, allocating time from both OR and surgeon and deciding on the surgery sequence, which corresponds to the *Allocation Scheduling* [12]. On the other hand, Meskens et al. [4] simplified the concepts and considered that planning (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 room, according to human and material resources' availability.

The aim of this work is developing a method that optimizes surgery planning and scheduling, considering the tactical decisions made, namely the MSS, surgeon's preferences and staff, room and downstream unit capacity. Although the problem to be solved is operational, both tactical and operational levels are considered in this review, since tactical decisions are considered in this work and there is the possibility of making tactical decisions as well.

In this chapter, a review of the existing, recent and relevant literature is assessed. To better organize the review, it is divided according to the decision level in the study and similar articles are grouped and presented chronologically. After presenting the tactical and operational level studies, in **Sections 3.1** and **3.2**, respectively, **Table 3.1** summarizes the methods utilized, namely the model, type of solution approaches and objectives considered. This table represents a condensed, but short and easy, reading of this review. Then, studies found interesting, but out of the scope of this work in terms of methods or problem approached, are presented in **Section 3.3**. In **Section 3.4** the strategies to handle the surgeon's preferences are also reviewed, since it is a novel feature of this work. Finally, conclusions and considerations, concerning the whole chapter, are presented in **Section 3.5**

3.1 Tactical Decisions - MSS

In this section, tactical decision level studies are detailed, including mathematical methods utilized, computational languages and aspects considered in the models.

In order to solve the MSS problem, Tànfani and Testi [11] apply a Binary Linear Programming (BLP) model and a heuristic algorithm, to assign the surgeries and patients to the corresponding wards, for a defined plan horizon. Waiting time, equipment availability, service capacity (number of Intensive Care Unit (ICU) beds for instance) and surgical team availability, are considered in the constraints. The BLP model objective function minimizes cost, while the heuristic algorithm takes into consideration the expected LOS and also aims at minimizing costs. The results are obtained using *MPL (Maximal Software 2000)* and *CPLEX*, and the heuristic is coded in *Visual C Language*. Computational experiments revealed that the heuristic approach can achieve levels of performance that enable a MSS for large departments, with extensive waiting lists. Therefore, it is concluded that the heuristic approach may outperform the BLP model.

To obtain the demand distribution related to the downstream unit, based on a MSS, Fügener et al. [13] utilize a stochastic approach, divided into three steps. First, the ICU patients distribution is calculated, for each specialty. Second, this distribution is obtained for a cyclical block. Finally, the MSS is introduced and the occupancy levels for the ICU and each ward are calculated. The main goal is minimizing costs associated with downstream units and a solution is reached through a Branch-and-Bound (BB) algorithm. Additionally, two different heuristic strategies provide feasible solutions to the scheduling problem. The first strategy involves techniques such as Simulated Annealing (SA), incremental improvement heuristic (IIH) and a 2-Opt heuristic. In the second strategy, the objective function is firstly achieved, based on expected values (EV) and then on expected values and variances (EVV). Only two of the methods correspond to a computational time of less than one hour (SA and EVV). The software utilized is the *IBM ILOG CPLEX Optimization Studio Version 12.2*.

Penn et al. [6] and Anjomshoa et al. [14] propose a method to solve the tactical problem, based on multiple criteria Mixed Integer Linear Programming (MILP) and an exact solution. Penn et al. [6] develop an objective function with a weighted sum of objectives, and change those weights according to the stakeholders' preferences. Aspects like the surgeons' availability and preferences, room type and its suitability for each procedure, equipment availability, reducing the maximum number of beds needed and allow the MSS cycle length variation are considered. On the other hand, Anjomshoa et al. [14] have as objectives overdue patients, waiting list and tardy days minimization and revenue maximization. Both studies include ICU and other resources capacity constraints, [6] considers demand constraints and [14] staff capacity constraints. Anjomshoa et al. [14] utilize a MSS base and boundaries between this and the MSS obtained through the model are set. Penn et al. [6] solve the model with a standard linear solver, the *FICO Express-IVE* and Anjomshoa et al. [14] design it using the *Optimization Programming Language* and implement it in the *IBM Decision Optimization Center* platform, which uses the *CPLEX* optimizer to solve it. Anjomshoa et al. [14] test their strategy in the Royal Children's Hospital in Melbourne, Australia.

To handle the tactical planning problem, Dellaert and Jeunet [15], similarly to [6, 14], develop a MILP model, but solve it using a Variable Neighborhood Search (VNS) algorithm, determining an admission plan for patients within a planning horizon. The solutions obtained using the algorithm and *CPLEX* solver are compared, concluding a better performance for the algorithm. The mains goals are to minimize over and under utilization of multiple resources, i.e., reach a target utilization. The resources include operating theaters, beds and human resources, specifically nurses. Real instances, from the Thorax Center Rotterdam, in Netherlands, are solved using *CPLEX* and *R-VNS* and *FD-VNS*, both coded in *C* language.

Kumar et al. [16] develop a model to optimize the MSS, through a Mixed Integer Programming (MIP) approach. The downstream unit capacity is considered as constraint, as well as resource availability and the first-come-first-served/cancel policies. The uncertainty is introduced in the model through the length of stay of the patients. Additionally, a simulation technique is implemented to provide an optimal MSS based on the most frequent optimal one and a Sample Average Approximation (SAA) technique to obtain a solution and compare it with the MSS obtained. From this last comparison, the SAA approach is not proven to achieve better results. The objective is mainly the maximization of the utilization level, taking into consideration boundaries related to cancellations.

To consider the uncertainty inherent in specific variables, Mhallah and Visintin [10] implement a

Stochastic Programming (SP) approach, having a two-week cyclic MSS, to define which scheduled specialty is attributed to each OR time block. The stochastic problem is handled in two stages, in which the first maximizes expected throughput and the second determines the optimal number of surgeries actually performed, using a BLP. This is done for specific stochastic variables values and several scenarios. The variables such as length of stay, intensive care unit time and surgical times are considered stochastic by this model. The objective function is optimized on average, through a SAA approach, giving the expected number of performed surgeries, within the ones scheduled, which represents the final result. The model is solved using *CPLEX*, evoked from *GAMS 25.0.2*. The results obtained are satisfying considering the threshold levels defined and show the importance of considering the stochastic nature of certain variables. The model is applied for the case study of the Meyer Children's Hospital in Florence, Italy.

Furthermore, some studies found integrate more than one decision level, namely [17], [18] and [19], all with different combinations of methods. Aringhieri et al. [17] include advance scheduling decisions and tactical ones, with a 0-1 Linear Programming (LP) model solved heuristically. Explicitly, the surgical specialties are assigned to OR time blocks and the patients from the waiting list are chosen to be scheduled. The objective function aims at minimizing waiting time and production costs. The bed capacity is considered, specially the weekend capacity. A two-level meta-heuristic approach is developed to obtain a solution, after proving the problem to be NP-hard. The method is coded in standard *C++* language and the computational tests are performed using *CPLEX 12.1.0*. Real data collected from the Department of General Surgery of a public hospital in Genova, Italy, is used for the testing and validation.

Guido and Conforti [18] integrate the operational and tactical levels, to assign surgical specialties and teams to operating rooms and perform admission planning and scheduling activities. The approach has multiple objectives, including the maximization of the number and overall clinical priority of scheduled patients and minimization of under-utilization of assigned OR blocks and costs, to implement a block scheduling strategy to manage the OR. The constraints include the rooms capacity and material resources, and the model allows updating the staff availability, waiting list status and work hours for the next planning period. The MILP model is also heuristically solved, through a hybrid genetic algorithm technique, by running the solver *IBM ILOG CPLEX Optimization Studio V12.5.1* and the model is coded in *C* language. Real data is used to test the model, from the General Hospital of Cosenza, in Italy.

Marques et al. [19] also mix the same two levels and use a MILP model. However, this model to build a MSS, is solved through exact methods. In an operational level, the MSS provides each surgery's individual schedule, including day, OR and time interval. In this case, the schedule is not cyclical, instead, a new schedule is implemented every week, or sometimes daily. It is considered that the schedule needs to be revised every three months, using data from the previous trimester, which guarantees the constant quality of the schedule. The model is solved on *DOcplexcloud*, the *Decision Optimization on Cloud*. Four optimization criteria are found based on the case study hospital's objectives. First, the balance between the number of patients sent daily to each unit. Then, concentrate as much as possible surgeons from the same specialty in the same OR and allocate specialties to OR time blocks when the maximum number of surgeons from that specialty is available. Finally, for a surgical specialty or surgeon, use the previous semester median time to assign in the following one. Uncertainty concerning the surgeries' time is included in the model. The decision maker can choose from a set of possible solutions, which is evaluated by the stakeholders.

3.2 Operational Decisions - Elective Surgery Scheduling

In this section advance scheduling studies are presented in the first subsection and allocation scheduling ones in the second. However, before those, studies that included both advance and allocation scheduling are presented.

In 2010, Fei et al. [20] propose a solution for the weekly planning problem of an OR running with an open scheduling strategy. The planning problem is assessed through a Column-Generation Based Heuristic (CGBH) approach. Then, a solution for the daily scheduling problem of the same OR is presented, through a Hybrid Genetic Algorithm (HGA). The model is described as a Set-Partitioning Integer Programming (SPIP) problem and its goals include minimization of both overtime costs and idle time and maximization of OR utilization. The downstream unit resources are considered as constraints. The CGBH solves the problem by choosing among an already defined group of feasible plans, a solution with quality. Real data is used for the model, from the University Hospital of Ambroise Paré, in Belgium. The software through which the model is written is the *Microsoft VC++ 2005 Express Edition* and the solver used is the linear programming solver *COIN-OR*.

Roland et al. [21] take into consideration an unusual factor, the medical staff well-being. With that in mind, the human resources capacity is stressed, to avoid medical staff exhaustion and dissatisfaction. A MIP model is proposed to obtain an optimal solution and a genetic approach to solve larger instances. Time and resources availability constraints are introduced and the objective consists in minimizing opening and overtime costs. The MIP model is coded in *Ampl* language linked with the *CPLEX* solver, while the genetic approach is written in *Matlab*.

For a specific case study hospital, Marques et al. [22] use an ILP model to create a weekly schedule, while maximizing the OR utilization. The main constraints considered are a fixed nursing team in each room and the hospital's tactical policy compliance. The surgeon is previously assigned to the patient, only allocating a room when building the schedule. Additionally, priority levels among the elective patients from the hospital's waiting list are considered. A simple improvement heuristic approach is implemented to the best feasible integer solution. The ILP model is solved using the optimizer *CPLEX 11.0* with *CONCERT 2.5 ILOG* and the heuristic is coded in *C++* language.

To compare two different optimization approaches, Mixed Integer Nonlinear Programming (MINLP) and Constraint Programming (CP), Zhao and Li [23] build two models to solve the daily scheduling problem. Three important factors are considered, namely the number of operating rooms to open, allocating each surgery to an OR and defining the surgery sequence. Different types of ORs are considered, i.e., rooms where only certain types of procedures are performed. The setup and surgery times are deterministic and the final goal of both models is to minimize the cost. Both models are built and solved by the software *IBM ILOG*, using the *CPLEX Optimizer* for the MINLP model and the *CP Optimizer* for the CP model. The main differences between the two tested models consists in the CP focus on constraints and feasibility, CP constraints can be logic and CP models use heuristics to eliminate infeasibilities and reduce search space. The CP model presents better computational time and solution quality, when compared with the MINLP one.

The same authors as in [22], propose in [24] an ILP model for a bicriteria version of a similar problem, now focusing on the Portuguese National Health Plan guidelines. Specifically, the two guidelines the study focuses on are reducing the waiting list and rationalizing the resources. With that in mind, the objectives of the model consist in maximizing the surgical suite occupation, similarly to [22] and the number of surgeries scheduled. The decisions now include not only assigning a room to each procedure, but also a date and a starting time, similar to [23]. The bicriteria heuristic approach includes a constructive heuristic and an improvement one and is coded in *C++* language.

Marques and Captivo [25] propose an evolutionary algorithm based on the single criterion version of the same problem presented in [22, 23] and incorporating the bicriteria heuristic in [24]. The evolutionary method is considered more suited for a surgical planner since it does not depend only on weights assigned by the decision maker. Instead, it generates multiple solutions from which the planner can choose. Similarly to previous work of the same authors, the model is coded in *C++* language.

To improve the health plan guidelines achievement, Marques et al. [26] develop and apply a genetic heuristic technique based on a Biased Random-Key Genetic Algorithm (BRKGA). In the present problem, an intervention date must be assigned as well as an operating room and a starting time, for each waiting patient, combining both advance and allocation scheduling. While solving the ILP problem, the optimization criteria considered are maximizing OR occupation and the number of scheduled surgeries. These criteria are handled independently, due to their conflicting nature, with two versions of a single objective genetic heuristic, and the problem is solved using the optimizer *CPLEX 12.4*. It is verified that the surgical plan quality increased and this approach requires less resources than the strategy being used. Furthermore, comparing to the authors' previous work concerning the same problem [22], this study presents improved computational time and solution quality, concluding that genetic heuristic approaches outperform linear programming ones, previously tested.

Saadouli et al. [27] propose a strategy to select the patients from the waiting list to be scheduled and assign them a room. Recovery beds and operating rooms are the resources considered in the model. Uncertainty is introduced through surgery duration and length of stay. For OR time allocation the problem is formulated as a knapsack problem, while for the room assignment a MIP model is used to describe the problem. The objective is minimizing the makespan. In another phase, a Discrete Event

Simulation (DES) model is implemented to assess the model's efficiency comparing to the professional's experience and practice. The model is based on the real situation of the Orthopedic Department of the Habib Bourguiba Hospital, in Tunisia.

Molina-Pariente et al. [28] and Vali-Siar et al. [29] approach the OR scheduling and planning problem by developing a MILP model solved exactly and heuristically. Both consider in the heuristic methods a constructive one, but Vali-Siar et al. [29] also present a meta-heuristic strategy using a GA. Concerning the objectives, both include tardiness and idle time minimization, adding in [28] the number of surgeries scheduled maximization and in [29] overtime minimization. Also for the two approaches, human and material resources are considered as constraints, however, Molina-Pariente et al. [28] also include room eligibility for each procedure. Vali-Siar et al. [29] consider the surgery duration and length of stay uncertain, handling it with a robust optimization technique. On the other hand, Molina-Pariente et al. [28] consider an interesting factor as they assume the surgery duration is affected by the surgical team experience and skill. Finally, the solvers used in [28] are *CPLEX 12.4* and *Gurobi 5.6*, being the second later chosen since it outperforms the first. In [29], the MILP model is written in *GAMS version 24.1.3* and solved using *CPLEX*, while the heuristic and meta-heuristic methods are coded in *MATLAB*. In both studies the heuristic methods outperform the exact ones, and in [29] the CH performs better than the GA.

Similarly to [28, 29], Wang et al. [30] define a MILP and solve it exactly and heuristically, to choose which rooms to open, allocate a room to each surgery and define a daily sequence. The objective function aims at minimizing operational costs, and the surgery duration is considered uncertain. The heuristic approach is utilized to build a feasible probability distribution and a Linear Decision Rule technique is applied to approximate the MILP model, due to long computational times associated with it. The model is written in *C#* language, on a *Visual Studio 2010* platform and the solver used is *CPLEX*.

Zhong et al. [31] and Burdett and Kozan [32] treat a surgical patient as a job that has to be processed, and both human and material resources needed to process the job as machines that have to work simultaneously. Therefore, the surgery scheduling problem, for a room, can be compared to a parallel machines scheduling problem. For an entire surgical service, with multiple rooms, it can be compared to a multiple parallel machine scheduling problem. The authors consider that scheduling is a NP-hard problem and that, consequently, only an approximate solution can be obtained. With that in mind, Zhong et al. [31] develop a two-stage model in which the first stage consists in allocating the surgeons to ORs while ensuring the surgery with the latest completion time is finished as soon as possible. The second stage includes the definition of the surgeon sequence in each room, aiming to minimize sum of the resources' costs.

Xiang et al. [33] and Burdett and Kozan [32] compare the operating room surgery scheduling problem with a multi-resource constraint flexible job-shop scheduling problem. Xiang et al. [33] provide an Ant Colony Optimization (ACO) method to solve the problem. Material resources and human resources, including respective surgical specialties and qualifications are included as constraints. The objective function aims at minimizing makespan, i.e., minimizing the time to finish all surgeries, obtaining sub-optimal solutions. The ACO algorithm is coded in *Matlab* and the *SIMIO* software is utilized to develop a DES model and generate schedules for further comparison with the ACO technique. On the other hand, Burdett and Kozan [32] include cancellations, postponements, delays, downstream unit and resources constraints, in a MIP model. Additionally, constructive algorithms and hybrid meta-heuristics are proposed, to address the sequencing and scheduling problems. The goal is makespan minimization and the model is written using the *C++* language. The model is tested using a case study from an Australian large tertiary teaching hospital, in Brisbane.

Several studies present a MILP or ILP (only in [34]) model, with a heuristic solving strategy, for different situations. [34–38]

Landa et al. [35] propose a two-phase approach, aiming at maximizing OR utilization and minimizing cancellations. Uncertainty is introduced in the model through the surgery duration and weekend capacities for both human resources and downstream units, are considered constraints. A hybrid solution approach combines a Monte Carlo Simulation with neighborhood search techniques and the algorithm is written using a standard *C++* language. The method is tested with a real instance, from the Department of General Surgery of the San Martino University Hospital, in Genova, Italy.

Riise et al. [36] propose a generalized model and some extensions for certain situations, such as a multi-project situation and resource constrained mode. The search method developed to solve the problem uses online learning in order to achieve a balance between construction and improvement computational loads. The objective function aims at minimizing makespan and the constraints considered include time and resource related constraints. Real data from Bærum Sykehus Hospital, in Norway, is utilized to test the model, which is solved using the *CPLEX* commercial solver.

Bam et al. [37] determine, on a daily basis, the number of ORs to open, the surgeon-OR assignment and the surgery sequence. A fast two-phase heuristic and a decomposition heuristic are implemented to solve the problem and, to evaluate the schedule under uncertainty, a discrete-event simulation approach is applied. The human resources, particularly surgeons, operating rooms and post-anesthesia care unit are considered in the method. The objective function minimizes the fixed costs of having a OR running. A mid-sized hospital partnered to be used as case study.

Díaz-López et al. [38] later mix optimization and simulation techniques, in a stochastic version, providing a set of possible solutions from which the Méderi University Hospital in Bogotá, Colombia can choose. The rooms are considered constraints and the objectives include minimizing delays and maximizing the rooms' use. After defining the surgeries' duration as a random variable, a Greedy Randomized Adaptive Search Procedure (GRASP) is applied. For the simulation phase, a Monte Carlo Simulation estimates indicators from the objectives. A solver *CPLEX 12.7* of *GAMS* solves the MILP model and the GRASP is implemented in *Visual Basic for Applications of Excel*.

Zhang et al. [34] aim at minimizing the total costs, with a two-level method. Uncertainty is considered for surgery duration, as well as for patient length of stay and new arrivals. The two-level model corresponds to a SP model and, using a SAA approach, it is translated into two solvable ILP problems. Both OR and downstream unit capacities are introduced as constraints. To solve the problem, an approximate dynamic programming approach, based on recursive least-squares temporal difference learning is developed. The method is modeled in *C++* language and the solver utilized is *Gurobi 7.5.2*.

3.2.1 Advance Scheduling

In this section, only the studies that search solutions for the advance scheduling problem are presented and detailed.

Lamiri et al. [2] develop an "almost exact" approach, by integrating a Monte Carlo Simulation technique and a MIP model, and an approximated one, including constructive and improvement heuristics and a SA heuristic as well. The OR capacity is assumed to be shared by elective and emergency surgeries. The goal is to decide which patients from the waiting list are going to be scheduled within a planning horizon, while minimizing a sum of different types of costs. All methods are coded in *MS Visual C#.NET 2003* and the SA approach is solved using the *ILOG CPLEX 11.0* library.

Min and Yih [39] resort to SP, considering the demand deterministic, and to a SAA approach to obtain an optimal schedule for elective surgeries. In the objective function, patient priority is introduced, through a score. The final goal is cost minimization, and the constraints include human and material resources capacity and downstream unit dimension. Moreover, the uncertainty is introduced as the surgery duration follows a discrete distribution in the model. The SAA algorithm is implemented in *C++* language and *ILOG CPLEX 11.0*. Additionally, a simulation study is conducted to compare a deterministic expected value with the solutions obtained resorting to the stochastic model. A better performance is verified for the stochastic model, justifying its additional computational time with a higher quality solution.

Jebali and Diabat [40] follow Min and Yih [39] work by considering the same resources and using similar approaches. However, the uncertainty considered is also related to the patient's length of stay. The method is implemented using the *MS Visual C++* connected with *ILOG CPLEX 12.3* library. To solve it, the *CPLEX* branch and cut algorithm is utilized.

Similarly, Razmi et al. [41] also develop a SP model, focusing on deciding which surgeries should be scheduled in a defined planning period. The objective function minimizes a sum a different types of costs. A SAA method is implemented, due to the problem's NP-hardness. An extension of the model is still defined to consider emergency surgeries, through a stochastic model. Besides having an exact solution, which can not be found within reasonable time for large instances, a meta-heuristic approach is presented, with a differential evolution algorithm. All methods are coded in *MATLAB 2009* and real data is obtained from Isfahan Kashani Hospital, in Iran.

Dios et al. [42] develop a Decision Support System for the University Hospital ”Virgen del Rocío” in Seville, Spain, to assist OR scheduling. The main decision is assigning each surgery from the waiting list, a period in which it should occur and the patient-surgeon pair should also be defined. 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. Specifically, a Two-stage Sorting Bin-Packing heuristic, a Mixed Two-stage Sorting Bin-Packing and a Random Extraction-Insertion algorithm. The model is solved using the commercial software *Gurobi version 5.6* with a stopping criterion.

Neyshabouri and Berg [43] consider uncertainty relevant in terms of length of stay and surgery duration. Therefore, both uncertainty sources are included in the model, that aims to minimize a weighted sum of costs. The downstream unit capacity is introduced as constraint. The model firstly formulated is then rewritten into a MILP model, to allow an easier solution. As solution method, a column-and-constraint generation technique is applied. All model experiments are coded using *Phyton* programming language and solved by the optimizer *Gurobi*.

Jebali and Diabat [44], similarly to Neyshabouri and Berg [43], introduce uncertainty concerning the length of stay and surgery duration. A Chance-Constrained Stochastic Programming (CCSP) model is developed to solve the planning problem and a SAA technique, as well as a Monte Carlo Simulation approach, are utilized to obtain a solution. They also include the downstream unit capacity as a constraint and, additionally, the operating rooms. The resource capacity allocated for emergencies is considered random, i.e., a source of uncertainty. The objective function minimizes a sum of costs. The algorithm is coded using *MS Visual C++* language, linked with *ILOG CPLEX 12.3* and the SAA models are solved with the *CPLEX* branch and cut algorithm.

Wang et al. [45] tackle the planning problem, by implementing a distributionally robust chance-constrained surgery planning model. Aiming at minimizing costs and peak demand of beds, a Chance-Constrained Programming (CCP) model is developed, and the decisions include choosing which rooms to open and allocating surgeries to rooms. As constraints, the OR capacity is considered and uncertainty is introduced through service time. The downstream unit resources are taken into consideration, as well as OR overtime, which is not as typical. The model is written using *Matlab* language, linked to the *IBM CPLEX 12.5* solver. Real data from a large public hospital in Beijing, China, is collected to evaluate the model's performance.

Roshanaei et al. [46] propose three Logic-based Benders' decomposition techniques and a cut propagation approach to solve IP models, that translate a location-allocation problem. In a large scale and aiming at cost minimization, the decisions include selecting patients and schedule them within a planning horizon and, simultaneously, determine the number of operating rooms to open. Factors such as priority scores, waiting times and current health status are taken into consideration in the model and material resources are consider as constraints. This decomposition method divides the problem into a master one and several sub-problems. For each sub-problem, a first-fit decreasing heuristic is applied, to faster obtain a feasible solution for the problem. The optimizer utilized is *Gurobi Optimizer (Gurobi, Inc.) v5.63*. Real data is collected from General Surgery Departments of the University Health Network hospitals, namely from Toronto, Canada.

Marques and Captivo [47] propose a systematic approach to change the scheduling policy, in a Portuguese hospital. The main goals include OR throughput maximization and enhancing the equity and access to patients, mainly by minimizing waiting times, while considering levels of clinical priority. Therefore, a MILP approach is developed to select the patients from the waiting list to be scheduled in a planning horizon, and assign a day, room and time block for each surgery. The model is developed for three different versions: the administration's, the surgeon's and a mixed version, each translating the corresponding stakeholder's point of view. Uncertainty related with surgery duration is introduced through a robust approach. All the MILP model versions are written in *C++* language, in *Microsoft Visual Studio 2010*, and solved using *IBM ILOG CPLEX 12.4*.

To continue the described study, Mateus et al. [48] utilize a local search heuristic approach to solve the same three versions of the surgical case assignment problem, within the same context, and afterwards compare its results with the ones in [47]. The heuristics are coded in *Java*, using the software *Eclipse Luna*. Some negotiations allow changes in each version of the problem. Concerning the heuristics developed, first a constructive heuristics returns an initial feasible solution and then an improvement heuristics, based on local search with different neighborhoods, reaches better solutions. The solutions found are considered high-quality and are achieved in a lower computational time, when compared with the ones obtained in [47].

Kamran et al. [12] propose a multiple objective approach to handle the advance scheduling problem. One relevant feature concerning this study is the fact that the scheduling policy considered is modified block scheduling, not often utilized. Taking emergency arrivals into consideration, the objectives include waiting time, tardiness, cancellations, block overtime and number of surgery days for each surgeon minimization. Uncertainty is taken into consideration when handling surgery duration, and both stochastic and deterministic versions of the problem are solved to allow comparison. A two-stage stochastic programming and a two-stage chance-constrained stochastic programming are developed and solved using a SAA approach and a Benders decomposition. All models are implemented using *GAMS 24.5* and solved by the *CPLEX* solver, and real data is used for experiments, from the Mehregan Hospital, in Qazvin, Iran.

Molina-Pariente et al. [49] develop a stochastic approach to solve the advance scheduling problem, using mixed integer programming. To solve the problem, Monte Carlo Simulation and SAA are utilized, aiming at cost minimization. Constraints include human and material resource availability. After applying the SAA technique, an iterative greedy local search method is also used to solve the problem. The commercial software *Gurobi version 5.6* is used to implement the problem.

3.2.2 Allocation Scheduling

The studies shown below concern only allocation scheduling problems and strategies to solve it.

Cardoen et al. [50], Pulido et al. [51] and Kroer et al. [52] propose MIP approaches for allocation scheduling, presenting different solution methods.

Cardoen et al. [50] propose both exact and heuristic MILP solution strategies. For an ambulatory surgery unit of a hospital, the model developed considers up and downstream units' capacities. The objectives include: prioritizing patients that have already been canceled once or that the surgeon has preference in operating first, embody the residence-hospital distance so that the ones further are not scheduled in the first morning slot, minimize the LOS of each patient, specially after the unit closes, so unnecessary hospitalizations are avoided and also, level the bed occupancy in the recovery unit so the corresponding staff has an also leveled workload. The model is written in *MS Visual C++ .NET* and connected with the *ILOG CPLEX 10.2* optimization library.

On the other hand, Pulido et al. [51] solve the problem only exactly. Under an open scheduling strategy, the surgery duration is considered deterministic and the model includes aspects such as surgeons' idle times, type of surgeon, potential overtime and operating room use. Moreover, a simulation method is implemented to assess different dispatching policies, concerning surgical procedures and surgeons. Aiming to minimize costs, the model is created by *AIMMS 3.14* software and a solution is obtained through the solver *Gurobi Optimization 5.5*. The simulation is done by the *Enterprise Dynamics 8.01 - INCONTROL Simulation Software*. As the case study is a teaching hospital, the staff expertise influences the results and should be included in the model.

Finally, Kroer et al. [52] implement a heuristic approach to handle the daily scheduling problem, using emergency surgeries as a source of uncertainty, along with surgery duration. The objective function includes minimization of overwork and open operating rooms. The constraints considered include patient priority, according to their condition, and different types of cleaning, according to the procedure and the patient. The two heuristic methods, 2-Step Relax-and-Fix and All Open Relax-and-Fix, are based on the MIP model and both are implemented using *ILOG CPLEX version 12.6*. Real data is used to test the model, from an anonymous hospital.

On a totally different point of view, Meskens et al. [4] attempt to solve the daily OR schedule problem, through a generic and modular model. This choice rises from the multiple real-life constraints associated with this problem, that should be included. To find a solution, a CP method is implemented, that minimizes makespan and overtime, while maximizing staff affinity. Therefore, the model's modules are the MSS, the surgical cases, material resources, human resources (surgeons, nurses and anesthesiologists), and the affinity between staff members, quantified through a score given by every surgical team member. Additionally, the surgeons' preferences, in terms of room and day to operate, are also considered. The "heart" of the model contains the constraints that connect the whole model. Concerning the objective function, the multiple objectives related with each module, are sequentially introduced, and after one objective optimization, this one is considered as constraint to the next optimization. CP shows significant advantages when performing for a highly constrained problem, as expected, since it parcels the search space. The model is implemented in *Java* and solved using a library of constraint satisfaction problems, *CHOCO*, added as the *Java library CHOCO 2.1.0* to the software.

In 2015, Wang et al. [3] present a comparison between MIP and CP approaches, to solve the daily scheduling problem. 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. Emergency surgeries are considered to have dedicated OR and team, so the method can be looked at as planning only elective surgeries, but with a smaller number of available rooms and teams. Both models minimize the time gaps in the schedule and in the MIP one, the constraints are linearized, which does not guarantee the model's effectiveness. The software *IBM ILOG* is used, with *CPLEX Optimizer* for the MIP method and *CP Optimizer* for the CP. The last, having a higher number of constraints, finds optimal solutions slower, but shows more efficiently the feasible ones.

Later, Latorre-Núñez et al. [53] also use MILP and CP models to handle allocation scheduling, this time using 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. The heuristic developed is based on a genetic algorithm and a constructive heuristic. Both MILP and CP models are coded in *C++* programming language, using *Win32 Console Application of Visual Studio 2010*, and the solver used is *CPLEX 12.6*. A run time limit is always imposed.

Silva et al. [54] and Wang et al. [55] solve heuristically the daily scheduling problem. Silva et al. [54] develop an IP model that focuses on considering each human resource specialty or specialized skill, as well as time windows for each staff member. This way, one particular characteristic of this study is the possibility of assigning anesthesiologists, two surgeries at the same time, if the operating rooms are compatible in terms of distance from each other. While Wang et al. [55] propose a LP model, two heuristic strategies, a SAA technique and a robust linear optimization one and three additional heuristics, concerning surgery duration. The goal in [54] is maximizing OR utilization and for [55] is minimizing a weighted sum of different types of costs. Wang et al. [55] include as constraints surgeon expertise, as senior surgeon have their surgeries scheduled first, and numerical experiments, with data from a large Chinese Hospital, are performed using the *Gurobi Python* interface from the solver *Gurobi Optimization (2016) version 7.0*. On the other hand, Silva et al. [54] base their model on a Brazilian Hospital situation and all models are written in *AMPL* and solved using *CPLEX 12.4*.

Bai et al. [56] and Hooshmand et al. [57] develop a SP method, heuristically solved, to handle the allocation scheduling and consider the surgery duration stochastic. Bai et al. [56] assume that each surgeon is assigned to an OR, include the downstream unit resources, the goal is to minimize the costs and consider uncertainty also in service time and LOS. While Hooshmand et al. [57], integrate both scheduling and rescheduling, allowing to easily achieve the goal, which is cost minimization. Bai et al. [56] present a Discrete-Event Dynamic System, to help formulate the stochastic problem and a sample gradient-based algorithm is implemented, to solve the SAA problem. On the other hand, Hooshmand et al. [57] propose a three-stage model for larger instances and to validate the GA performance. In [56], the algorithm is coded in *C++* language and solved using the *CPLEX* solver and, in [57], the model is coded in *AIMMS* software and solved in the *ILOG CPLEX 12.4* solver included in the *AIMMS* software.

Furthermore, Belkhamsa et al. [58] also develop a stochastic method solveD through heuristic methods, like in [56, 57], to solve the daily scheduling problem. An Iterative Local Search (ILS) method and a HGA are presented and compared. The hybrid technique combines a genetic algorithm with local search methods. Multiple constraints are considered, including human and material resources, up and downstream unit resources, no-wait times between stages and surgical specialties, for multiple stages, specifically the preoperative, intraoperative and postoperative ones. Concerning the objective function, it minimizes both total idle time and makepsan (maximum end time). Due to considering multiple resource constraints and stages, this problem is compared with a flexible multiprocessor job-shop problem with three successive phases, which has also been seen in this area [32, 33].

Table 3.1: Summary of the reviewed studies in **Sections 3.2** and **3.1**.

REFERENCE	*MODEL APPROACH*	*SOLUTION APPROACH*	*OBJECTIVE*
Decision Level: Tactical			
Tànfani and Testi [11]	BLP	Exact & Heuristic	1
Fügener et al. [13]	LP(SBB)	Exact & Heuristic	1
Penn et al. [6]	MILP	Exact	10-16
Anjomshoa et al. [14]	MILP	Exact	6-7-8-16
Dellaert and Jeunet [15]	MILP	Exact & Heuristic	4-5
Kumar et al. [16]	MIP	Heuristic	9
Mhallah and Visintin [10]	SP & BLP	Exact	6-16
Aringhieri et al. [17]	BLP	Heuristic	1
Guido and Conforti [18]	MILP	Heuristic	2-4-16
Marques et al. [19]	MILP	Exact	11-12-13-16
Decision Level: Operational			
Fei et al. [20]	SPIP	Heuristic	1-9-14
Roland et al. [21]	MIP	Exact & Heuristic	1
Marques et al. [22]	ILP	Exact & Heuristic	9
Zhao and Li [23]	MINL & CP	Exact & Heuristic	1
Marques et al. [24]	ILP	Heuristic	9-2
Marques and Captivo [25]	ILP	Heuristic	9-2
Marques et al. [26]	ILP	Heuristic	9-2

REFERENCE	*MODEL APPROACH*	*SOLUTION APPROACH*	*OBJECTIVE*
Saadouli et al. [27]	MIP & KP	Exact & Heuristic	3
Molina-Pariente et al. [28]	MILP	Exact & Heuristic	2-7-14
Vali-Siar et al. [29]	MILP	Exact & Heuristic	7-14-16
Wang et al. [30]	MILP	Exact & Heuristic	1
Zhong et al. [31]	IP	Heuristic	1-16
Xiang et al. [33]	Not described	Heuristic	3
Burdett and Kozan [32]	MIP	Exact & Heuristic	3
Landa et al. [35]	ILP	Exact & Heuristic	9-15
Riise et al. [36]	MILP	Heuristic	3
Bam et al. [37]	MILP	Heuristic	1
Díaz-López et al. [38]	MILP	Heuristic	7-9
Zhang et al. [34]	ILP	Heuristic	1
Advance Scheduling			
Lamiri et al. [2]	MIP	Exact & Heuristic	1
Min and Yih [39]	SP	Heuristic	1
Jebali and Diabat [40]	SP	Heuristic	1
Razmi et al. [41]	SP	Exact & Heuristic	1
Dios et al. [42]	MILP	Exact & Heuristic	16
Neyshabouri and Berg [43]	MILP	Exact	1
Jebali and Diabat [44]	CCSP	Heuristic	1
Wang et al. [45]	CCP	Exact	1-11
Roshanaei et al. [46]	IP	Exact & Heuristic	1
Marques and Captivo [47]	MILP	Exact	6-16
Mateus et al. [48]	MILP	Heuristic	6-16
Kamran et al. [12]	SP & CCP	Heuristic	7-15-16
Molina-Pariente et al. [49]	MIP	Heuristic	1
Allocation Scheduling			
Cardoen et al. [50]	MILP	Exact & Heuristic	10-11-16
Pulido et al. [51]	MILP	Exact	1
Kroer et al. [52]	MIP	Heuristic	16
Meskens et al. [4]	CP	Exact	3-16
Wang et al. [3]	MIP & CP	Exact & Heuristic	16
Latorre-Núñez et al. [53]	MILP & CP	Exact & Heuristic	3
Silva et al. [54]	IP	Heuristic	9
Wang et al. [55]	LP	Heuristic	1
Bai et al. [56]	SP	Heuristic	1
Hooshmand et al. [57]	SP	Heuristic	1

REFERENCE	MODEL APPROACH	SOLUTION APPROACH	OBJECTIVE
Belkhamsa et al. [58]	Not described	Heuristic	3-14

1 - cost minimization; 2 - number of surgeries scheduled maximization; 3 - makespan minimization; 4 - under-utilization minimization; 5 - over-utilization minimization; 6 - revenue maximization; 7 - tardiness minimization; 8 - waiting list minimization; 9 - utilization maximization; 10 - surgeon's preferences; 11 - workload variability minimization; 12 - number of rooms assigned to specialty minimization; 13 - MSS compliance maximization; 14 - idle time minimization; 15 - cancellation minimization; 16 - other(s)

Some objectives are not detailed and mentioned as ”others”, since those are maybe utilized only once without relevance or, in that study, are not important when compared to the rest.

3.3 Other Interesting Studies

In this section are studies found interesting, but not as relevant as the ones presented above, for the present work. These studies either solve problems out of the scope of this study, or implement methods to solve the OR scheduling and planning problem that are not relevant for this work.

Castro and Marques [59] propose a two-level decomposition algorithm, to obtain approximated solutions for elective surgery scheduling, based on Generalized Disjunctive Programming models. The goals are to maximize total surgical time and number of scheduled surgeries. Strategic, tactical and operational levels are mixed in the study, which is not only an innovative feature but also an exclusion criteria within the scope of this work.

Duma and Aringhieri [60] handle an unusual issue, as they propose a model for Real Time Management, that consists essentially in supervising the execution of a schedule, which is not approached in this work. It represents an online approach for surgery process scheduling, which is also innovative. To solve the operational problem, a hybrid simulation and optimization method is implemented, considering the stochastic nature in patient arrival, LOS and operating times.

Turhan and Bilgen [61] propose a solution to the Patient Admission Scheduling problem, for which a bed is assigned to each elective patient. Predicted LOS and the patient's preference are considered in the model. The solving technique includes two MIP based heuristics, a Fix-and-Relax and a Fix-and-Optimize, to decompose the problem and optimize its sub-problems. This problem is not usually assessed, therefore the study becomes interesting. However, it is not compatible with the scope of this work.

M'Hallah and Al-Roomi [62] considered off-line planning and on-line scheduling of operating rooms, within the operational decision level. Specifically, it includes room assignment to elective surgeries and surgical team assignment and sequence determination, for the sets of surgeries assigned to each room. The goals are enhancing under and over utilization of the operating rooms and the strategy developed consists in a simulation approach. This type of strategy is not included in this work.

3.4 Surgeon's Preferences

Since the surgeon's preferences are an uncommon factor to consider, and a novel feature in this work, the studies, in which these preferences are included, are assessed. The way these preferences are introduced in the model is detailed, also to compare with the intended strategy to include them in this study.

To translate the surgeon's preferences, and, in some cases, also the nurse's and anesthesiologists', a binary matrix is frequently used. In those, 1 means the surgeon is available in that time slot, or that time slot belongs to their preferences, whereas 0 is handled as unavailability. This way, their preference are always respected since it is treated as availability. After having the preference matrix and the schedule matrix, which is also binary and presents the value 1 when for that time slot, that surgeon has a surgery (the room may also be included), the constraint that translates the preference is a relationship between these two matrices. In no case the value from the schedule matrix can be higher than the preference matrix corresponding value, since that would mean a surgery is scheduled for a time slot that surgeon is not available [3, 4].

A simpler approach is implemented by Silva et al. [5], that essentially consists of gathering the set of periods for which the surgeon is available to begin a surgery, and the set of periods in which the surgeries begin. Considering these sets, it has to be ensured that the set of the periods in which the surgeries begin, consists in a subset of the set of periods in which the surgeon is available, while both are subsets of the daily periods set.

To the best of knowledge, the surgeon's preferences are usually handled as a constraint of the model, and not included in the objective function. Only Penn et al. [6] consider these preferences in one of the objectives, in 2017, which was then a novel feature in the literature. The preferences considered, and found by the authors in the literature, include the room, day or time block preferences, which is collected by interviewing each professional. This feature is not successfully introduced as the authors initially intended, but the surgeon's preferences are still considered in the model.

It is also essential to assess what has been done, in terms of masters thesis, related to the scope of this work. Ramos [63] introduces the surgeon's preferences in the OR planning and scheduling of elective patients, as it is intended to present in this work. However, the approach followed in [63] consists in a Decision Support Model, and not in an optimization mathematical model, in which the surgeon's scheduling decisions are modeled, through process mapping.

Besides being rarely considered in the literature, it is not found a study in which respecting the surgeon's preferences is part of the objectives in the same way it is handled in the model proposed in **Chapter 4**. The goal in this work is to attend their specific request in terms of day, time and staff members preferences, instead of simply try to schedule the surgery for a preferable room or time block, in a day.

3.5 Chapter Conclusions

It can be inferred that, heuristic methods only have to be implemented, when the exact methods are not enough to reach an optimal solution in useful time. There are aspects that are almost always 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.

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. Nevertheless, it is not mentioned as a concern by the stakeholders, and is not considered in this study. The main concern in the developed model is 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.

The model approach most commonly used, to develop models for OR planning and scheduling problems, is MILP, which consists in a case of ILP. In this case, the approach presented in **Chapter 4** is an example of an ILP model.

In the next chapter, the mathematical model is detailed, including parameters and variables, objective function and constraints.

Chapter 4

Mathematical Model

In the present chapter, an ILP model, developed to solve the scheduling problem related to the case study, is displayed.

The following developed model takes into consideration the tactical decisions made by the administration, namely, the MSS built by the head staff of the hospital's surgical service. Then, 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 timeslots for the surgery. This objective is controlled with weights, allowing to change the flexibility of both components. The goal is to find the balance between satisfying the surgeons, by providing what they ask, and following the MSS created by the hospital.

The model optimizes the weekly schedule, based on the surgical proposals presented by the surgeons and correspondent group of patients. The hospital's facilities, including the surgical floor capacity, and the staff needed to perform the surgery, namely anesthesiologists and nurses, are taken into consideration. The decisions include, not only the room and time for each surgery, but also the anesthesiologist and nurses assignment, guaranteeing both the MSS and the surgeons' preferences are considered in the decisions. The problem and model are represented in **Figure 4.1** in a schematic way.

As considered by Penn et al. [6], the stochastic nature of aspects like the surgery duration is not considered, since the hospital would lose interest in the model's utilization. The introduction of uncertain factors increases the model's complexity and its computational time, while the hospital is looking for an easy and fast tool.

The remaining content of this chapter describes the notation and assumptions made (**Section 4.1**) and the numerical model (**Section 4.2**), including objective function and constraints.

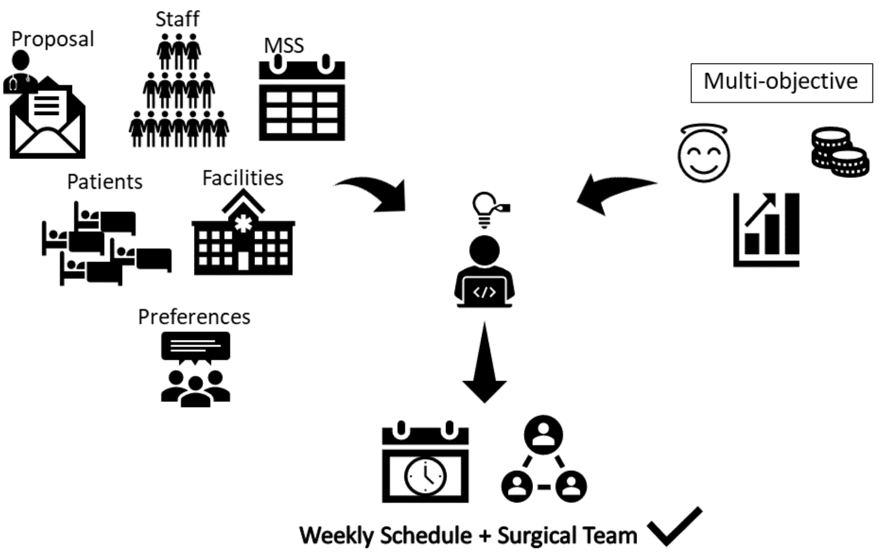

Figure 4.1: Schematic representation of the problem

4.1 Notation and Assumptions

Before developing the mathematical model, assumptions have to be made and considered. Also, the complete notation, including parameters and variables, has to be defined.

4.1.1 Assumptions

Some assumptions are considered, to facilitate the model writing, without compromising the solution's quality and the objectives achievement.

Firstly, internal surgeons are the ones that are in fact employees of the hospital. This distinction has to be made, since the external ones, are the surgeons that only go to the hospital to perform their surgeries. The internal surgeons are assumed to only work in that hospital. This way, in all existent timeslots in the schedule, they are available, or at least in the timeslots that correspond to the surgeon's specialty. The surgery duration includes cleanup time and turnover between surgeries, so this way, surgeries are scheduled consecutively. Additionally, this duration definition allows the staff to be scheduled in consecutive timeslots, in different rooms. In reality, the staff members are not in the room for the entire surgery duration, so they have time to change room, scrub in again and even to take a break, also essential.

Delays and cancellations are not considered in the model. At the scheduled time the surgical team, as well as the equipment and patient, are ready to begin the procedure. In addition, material resources needed for each procedure are considered always available. The pair surgeon-patient/surgery is assumed to already be defined. As the surgeon is the one to submit the surgical proposal, there is no need to determine which surgeon is performing that surgery. Finally, extra hours are not allowed, i.e., surgeries are scheduled to start and end within the surgical service opening and closing hours. Consequently, a surgery with a duration higher than the total daily functioning hours of the service, is not scheduled by the model. In practical terms, the probability of existing a surgery with that dimension is extremely low.

Another important aspect to mention, are the assistant surgeons. Usually, for each surgery, the responsible surgeon is not alone performing the surgery. Instead, often two surgeons perform a common procedure, the responsible surgeon and an assistant. Complex procedures usually require bigger teams, with more than two surgeons. However, this assistant surgeon is not considered in the schedule, and only one surgeon will be associated with each surgery. First of all, the surgeons are not the human resource that constraints the scheduling process. Considering the responsible surgeon available for the time block he/she requested in the OR, if the anesthesiologist and the nurses are available to perform the surgery, another surgeon is most likely to also be available, since the hardest available resources are anesthesiologists and nurses. Furthermore, assistant surgeons are usually younger and less experient surgeons, which means their availability is even more probable, since they usually have less patients than older surgeons. Additionally, the two surgeons needed for a procedure are usually from the same surgical specialty, and the same specialty usually needs the same material, which is only in one operating room. Therefore, the assistant surgeon is not likely to be performing other surgery, in another room at the same time, reinforcing the probability of being available.

4.1.2 Notation

Table 4.1 summarizes the notation utilized in the model. To express the number of elements in a set, the symbol $|.|$is used (for example: the number of elements of S, is $|S|$). In each set, including the surgeries, surgeons, anesthesiologists, nurses, operating rooms and surgical specialties, each entry is given an ID number. In the sets related to the days of the week and daily timeslots, the entries are sequential, since the two sets represent time components of the model.

4.2 Numerical Model

The multiple objectives are displayed in (4.1), (4.2) and (4.3), which are all maximized. In (4.1) the number of surgeries scheduled for the week is maximized and in (4.2) the profit from those surgeries is also maximized. The objective function in (4.3) 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 is given to them in the final schedule. The day and time for the surgery, anesthesi-

Table 4.1: 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
ζ_{er}	1 if surgical specialty e can be scheduled in room r due to fixed material, 0 otherwise
σ_{dr}	1 if room r is open in day d, 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

ologist 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, than the model only follows one of the objectives, being considered rigid. On the other hand, by introducing non-zero weights for both objectives, the model's flexibility increases. The three objectives are combined, in a single objective function, that maximizes the sum of all objectives.

$$\text{Maximize} \quad \sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\alpha^{start}_{sdtr} \tag{4.1}$$

$$\text{Maximize} \quad \sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}p_s \times \alpha^{start}_{sdtr} \tag{4.2}$$

$$\text{Maximize} \quad k_1\left(\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\mu_{sdt}\times\alpha_{sdtr} + \sum_{a\in A}\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\mu_{asdt}\times\lambda_{asdt} + \right.$$

$$\left. + \sum_{n\in N}\sum_{s\in S}\sum_{d\in D}\sum_{t\in T}\mu_{nsdt}\times\beta_{nsdt}\right) + k_2\left(\sum_{s\in S}\sum_{e\in E}\sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\theta_{se}\times\nu_{edtr}\times\alpha_{sdtr}\right) \tag{4.3}$$

$$\text{subject to :} \quad \sum_{d\in D}\sum_{t\in T}\sum_{r\in R}\alpha^{start}_{sdtr} \le 1, \quad \forall s\in S \tag{4.4}$$

$$\sum_{s\in S}\alpha_{sdtr} \le \sigma_{dr}, \quad \forall d\in D, t\in T, r\in R \tag{4.5}$$

$$\alpha_{sdtr} \ge \alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, t\in T, r\in R \tag{4.6}$$

$$\alpha_{sdtr} \le \theta_{se}\times\zeta_{er}, \quad \forall s\in S, d\in D, t\in T, r\in R, e\in E \tag{4.7}$$

$$\sum_{d\in D}\sum_{r\in R}\alpha^{start}_{sdtr} = 0, \quad \forall s\in S, t = \mid T\mid -d_s+1,...,\mid T\mid \tag{4.8}$$

$$\sum_{t'=t}^{t+d_s-1}\alpha_{sdt'r} \ge d_s\times\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, r\in R, t=1,...,\mid T\mid -d_s+1 \tag{4.9}$$

$$\sum_{t\in T}\alpha_{sdtr} = d_s\times\sum_{t\in T}\alpha^{start}_{sdtr}, \quad \forall s\in S, d\in D, r\in R \tag{4.10}$$

$$\sum_{s\in S}\delta_{csdt} \le 1, \quad \forall c\in C, d\in D, t\in T \tag{4.11}$$

$$\sum_{s\in S}\beta_{nsdt} \le 1, \quad \forall n\in N, d\in D, t\in T \tag{4.12}$$

$$\sum_{s\in S}\lambda_{asdt} \le 1, \quad \forall a\in A, d\in D, t\in T \tag{4.13}$$

$$\sum_{c\in C_s}\delta_{csdt} = \sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{4.14}$$

$$\sum_{a\in A}\lambda_{asdt} = \sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{4.15}$$

$$\sum_{n\in N}\beta_{nsdt} = nn\sum_{r\in R}\alpha_{sdtr}, \quad \forall s\in S, d\in D, t\in T \tag{4.16}$$

$$\sum_{d \in D} \sum_{t \in T} \lambda_{asdt} = d_s \sum_{d \in D} \sum_{t \in T} \lambda_{asdt}^{start}, \quad \forall s \in S, a \in A \tag{4.17}$$

$$\sum_{d \in D} \sum_{t \in T} \beta_{nsdt} = d_s \sum_{d \in D} \sum_{t \in T} \beta_{nsdt}^{start}, \quad \forall s \in S, n \in N \tag{4.18}$$

$$\sum_{a \in A} \lambda_{asdt}^{start} = \sum_{r \in R} \alpha_{sdtr}^{start}, \quad \forall s \in S, d \in D, t \in T \tag{4.19}$$

$$\sum_{n \in N} \beta_{nsdt}^{start} = nn \sum_{r \in R} \alpha_{sdtr}^{start}, \quad \forall s \in S, d \in D, t \in T \tag{4.20}$$

$$\sum_{s \in S} \sum_{r \in R} \alpha_{sdtr} \leq \mid R \mid, \quad \forall d \in D, t \in T \tag{4.21}$$

$$\sum_{s \in S} \sum_{r \in R} \alpha_{sdtr} \leq \frac{\mid N \mid}{nn}, \quad \forall d \in D, t \in T \tag{4.22}$$

$$\sum_{s \in S} \sum_{r \in R} \alpha_{sdtr} \leq \mid A \mid, \quad \forall d \in D, t \in T \tag{4.23}$$

$$\sum_{s \in S_b} \sum_{t \in T} \sum_{r \in R} \alpha_{sdtr}^{start} \leq ba, \quad \forall d \in D \tag{4.24}$$

$$\alpha_{sdtr}, \alpha_{sdtr}^{start}, \lambda_{asdt}, \lambda_{asdt}^{start}, \beta_{nsdt}, \beta_{nsdt}^{start}, \delta_{csdt} \in \{0,1\},$$
$$\forall s \in S, d \in D, t \in T, r \in R, a \in A, n \in N, c \in C \tag{4.25}$$

Constraints (4.4) ensure that all surgeries in the waiting list are scheduled at most once. Constraints (4.5) ensure two things at the same time. First, that surgeries can not be scheduled in a closed room. 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 (4.6) 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. In other words, if a surgery is scheduled to start in a certain timeslot, the patient is occupying the room in that timeslot, connecting the starting and occupation variables. Constraints (4.7) ensure that the surgeries are only scheduled for the rooms in which the correspondent specialty can be scheduled, due to fixed material constraints (type of room). This is based on each surgery specialty and the material that can not be transported.

It is still necessary to make sure that a surgery does not start in a timeslot that does not have enough following ones, to let the surgery be completed. With that in mind, constraints (4.8) deal with this, not allowing the start of each surgery from a certain timeslot on, specifically from the $\mid T \mid$-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 (4.9) 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 (4.10) make sure that for each surgery/patient, the OR time allocated is equal to the surgery duration estimate.

Constraints (4.11), (4.12) and (4.13) assure that each surgeon, nurse and anesthesiologist respectively, participate at most in one surgery at any point in time. Constraints (4.14) 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 (4.15) and (4.16), respectively. Similarly to constraints (4.10), constraints (4.17) and (4.18) ensure the anesthesiologists and nursing staff allocated OR time, respectively, is exactly the surgery duration. The constraints (4.19) 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 (4.20).

Constraints (4.21) make sure that, at any point in time, the number of surgeries happening does not exceed the number of functioning operating rooms in the surgical service. The same is assured by constraints (4.22) and (4.23), for the nurses and anesthesiologists, respectively, so that at any point in time, the number of surgeries being performed does not exceed the team capacity. The downstream unit capacity can not be exceeded as well, which is ensured by constraints (4.24), similar to what is done in constraints (4.21).

4.3 Chapter Conclusions

The present chapter shows the developed mathematical model, intended to optimize the OR weekly schedule. It takes into consideration staff, room and postoperative beds capacity. Also, specific case study restrictions are included, like fixed material constraints, in which the room to schedule a surgery must be defined by the surgery's specialty and the material necessary. Objective wise, the model maximizes 3 objectives. The first two consist in maximizing the number of surgeries scheduled and the profit generated. The third and main objective, maximizes the MSS compliance and the surgeon's preferences, through the use of weights associated with each part, allowing to find a balance in this objective.

In the following two chapters, numerical experiments are performed, and its results are presented, followed by result analysis. In **Chapter 5**, the model is technically validated using two toy instances. Then, in **Chapter 6**, a real instance, based on data from the hospital, is described and the results using that instance are presented. In addition, in that chapter, the hospital validation, with a stakeholder, is discussed, and managerial insights included.

Chapter 5

Model Validation with Toy Instances

This chapter aims at technically validate the ILP model developed in **Chapter 4**, using two toy instances. Firstly, the instances are described in **Section 5.1**. Then, the results using these instances, are discussed in **Section 5.2**.

The model is implemented in *Java*, through the *Eclipse IDE* (Integrated Development Environment). *Eclipse* encases 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 Windows 10 Home.

5.1 Toy Instances Description

Toy instances must be complex enough to allow grounded conclusions about the model's robustness. On the other hand, they should also be simple enough to know which results to expect. Two toy instances are designed, to have multiple results. The values and parameters equal in both toy instances are detailed in **Tables 5.1, 5.2**, **5.3** and **5.4**. The features that distinguish them are then described, for the first and second toy instances.

σ_{dr} represents which operating rooms are open and closed, in each day, and is described in **Table 5.2**. Saturday is the only day for which one room is closed, since it usually has a lower number of surgeries to be scheduled. For Saturday, only two rooms are included in the MSS, so those are obligated to open. Therefore, one random room, from the ones left out of the MSS, is chosen to be closed in that day.

The parameter ζ_{er}, that has the value 1 if a room r has the fixed material needed for a surgery of the specialty e, and 0 otherwise, is equal for both toy instances. This parameter translates if a surgical

Table 5.1: Parameters equal for the two toy instances.

Parameter	Value	Details
$\|D\|$	6	Number of days to schedule the surgeries. A weekly schedule is considered, from Monday until Saturday.
$\|A\|$	4	Number of anesthesiologists available.
$\|N\|$	15	Number of nurses available.
$\|R\|$	4	Number of operating rooms open to schedule the surgeries.
$\|E\|$	9	Number of surgical specialties associated with the surgeries to schedule.
$\|T\|$	28	Number of daily timeslots available to schedule the surgeries. This parameter is calculated considering that the OR opens at 8a.m. and closes at 10p.m., and the timeslot time interval is 30 minutes.
nn	2	Number of nurses needed to assist a surgery.
ba	20	Number of beds available in the postoperative care.

Table 5.2: Parameter σ_{dr} for the two toy instances

Day\Room	*1*	*2*	*3*	*4*
1	OPEN	OPEN	OPEN	OPEN
2	OPEN	OPEN	OPEN	OPEN
3	OPEN	OPEN	OPEN	OPEN
4	OPEN	OPEN	OPEN	OPEN
5	OPEN	OPEN	OPEN	OPEN
6	OPEN	OPEN	CLOSED	OPEN

specialty can be scheduled in a certain operating room or not and is described in **Table 5.3**.

Finally, the parameter that translates the MSS, ν_{edtr}, is also the same for both instances, and is presented in **Table 5.4**. The morning shift refers to the period between 8a.m. and 4p.m., while the afternoon shift starts at 4p.m., ending at 10p.m. In shifts without a specialty specified, like Saturday's morning shift in Room 1 and afternoon shift in Room 4, all specialties are allowed to be scheduled. The MSS and parameter ζ_{er} (**Table 5.3**) both translate permission to schedule a specialty in a room. These can be quite similar, however they both need to be considered. The difference is in the fact that the MSS specifies hours, or shifts, while ζ_{er} only considers rooms. In addition, ζ_{er} is included in

Table 5.3: Parameter ζ_{er} for the two toy instances

Specialty\Room	*1*	*2*	*3*	*4*
1	✗	✗	✗	✓
2	✓	✗	✗	✗
3	✓	✓	✓	✓
4	✓	✓	✓	✓
5	✗	✓	✗	✗
6	✗	✓	✗	✗
7	✓	✓	✓	✓
8	✓	✓	✓	✓
9	✓	✗	✗	✗

✓ - specialty can be scheduled in room; ✗ - otherwise

Table 5.4: Weekly Master Surgery Schedule for the two toy instances.

	Day 1 - Day 5				Day 6	
	Room 1	Room 2	Room 3	Room 4	Room 1	Room 4
Morning shift	Specialty 2	Specialty 5	Specialty 3	Specialty 1	-	Specialty 7
Afternoon shift	Specialty 9	Specialty 6	Specialties 7+8	Specialty 4	Specialty 3	-

a constraint, because it must be respected for all surgeries, while the MSS is included in a objective, which is intended to be maximized, but is not respected in all situations.

In the first toy instance, 30 surgeries are included to be scheduled, 19 of them inpatients, which means they are occupying a bed in the postoperative unit. Concerning the staff capacity, 10 surgeons are considered. The second toy instance has 58 surgeries to schedule, 37 of them are inpatient cases, and 12 surgeons make the hospital's surgeons team. The first 30 surgeries from the second toy instance are the ones from the first. The remaining 28 surgeries are newly generated. Thus, only these new 28 are included in the tables correspondent to the second toy instance.

Due to the extension of the information of these two instances, the description of both is in **Appendix A**. The parameter θ_{se}, which connects each surgery to its specialty, is on the left side of **Table A.1**, for the first toy instance, and of **Table A.2**, for the second. In these tables, on the right side, is the responsible surgeon for each surgery. For all surgeries, a duration in timeslots and a profit value in Euros are generated randomly, which correspond to the parameters d_s and p_s, respectively. Additionally, the requested hour and day, that represents parameter μ_{sdt}, requested anesthesiologist (μ_{asdt}) and nurses (μ_{nsdt}) are also detailed for each surgery. All these parameters are in **Table A.3**, for the first toy instance, and in **Table A.4**, for the second.

5.2 Results using the Toy Instances

In this section, the two toy instances are used to technically validate the model, and its results are presented. With both toy instances, a feasible solution is reached. The model shows a total running time higher, for the second toy instance, which may be explained by the higher number of surgeries to schedule. The model's behavior is considered satisfactory, respecting all the constraints and following the objectives imposed, as it will be proven further. The computational results for both toy instances are detailed in **Table 5.5**, including results with different k_1 and k_2 weights. These results include the number of variables and constrains for each toy instance. For each test performed, the total running time, the gap value, the best bound, the overall objective value and each objective values are presented.

Firstly, it is important to mention the different weight values used for the second toy instance, in one of the cases. For the analysis in which the values should be k_1 = 0 and k_2 = 1, the values utilized are

Table 5.5: 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(*)	
Number of surgeries scheduled	*0.5*	*0.5*	30.0		58.0	
	1	*0*	30.0		58.0	
	0	*1*	30.0		58.0(*)	
Profit	*0.5*	*0.5*	43 927.55		82 497.46	
	1	*0*	43 927.55		82 497.46	
	0	*1*	43 927.55		82 497.46(*)	
MSS vs. Surgeon's Preferences	*0.5*	*0.5*	550*k_1 94*k_2	322	981*k_1 186*k_2	583.5
	1	*0*	556*k_1 82*k_2	556	1001*k_1 120*k_2	1001
	0	*1*	6*k_1 147*k_2	147	556*k_1 300*k_2	313.3(*)

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

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. Although it is expected, for k_1 = 0, that the surgeon's preferences are ignored, for k_1 = 0.05, these must also be highly neglected. In addition, for a k_2 = 0.95, the MSS is expected to be significantly prioritized.

In terms of running times, the ones corresponding to the second toy instances are higher than the ones related to the first toy instance. This is expected, due to the higher dimension of the second toy instance, as it contains almost twice the number of surgeries than the first. 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. Nevertheless, this time difference is not expected. In the second toy instance case, the time for the equal weights is significantly lower, as the goals are probably easier to achieve.

The gap value is equal for almost all tests, for the two instances, with a value of 0.01%. Although the gap achieved is not zero, the value is considered satisfactory. 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 optimal gap value is achieved.

Concerning the objective values, no relevant information can be concluded only from the global objective value. Therefore, the three objectives are detailed. For the first objective, that maximizes the number of surgeries scheduled, it can be easily concluded that it is always maximized, for both instances. This is easy to see, since this objective value is equal to the number of surgeries in the waiting list to be scheduled. Similarly to the first, the second objective maximization is also easily observed. This objective, related to the profit maximization, has a value that corresponds to the sum of all profit values, for all the surgeries in the set.

On the other hand, conclusions are not easy to make about the third objective value. This objective value is obtained through a count of the variables and parameters entries, which is different for each objective part. Its first part, related to the surgeon's requests, not only includes the day and hour for each surgery, but also the staff members chosen. The second part, related to the MSS, includes day, hour and room. Naturally, if half the surgeries is scheduled according to the MSS, and the other half respecting the surgeon's request, the values of each part are not expected to be equal. Therefore, these values can not be directly compared. Due to the complexity related to this objective value, a comparison between the resulting schedules, for different weights, is performed further, for both toy instances.

The first toy instance is mainly designed to test if the model is creating the weekly schedule in the right way. This means, scheduling the surgeries in sequential timeslots, according to their estimated duration, in only one room and one day. The schedule can not allow overlapped surgeries, occurring at the same day and room, and also not overlapped work for any staff member. It is also possible to conclude if the surgeon assigned for each surgery corresponds to the responsible surgeon. Additionally, conclusions about the team assigned to each surgery are also possible to make.

The second toy instance contains almost twice the number of surgeries to schedule, comparing to the first. In this second instance, although the number of surgeries increases significantly, the staff capacity remains almost the same, only the number of surgeons increases by 2 surgeons, and the remaining resources maintain their capacity. The instance's dimension is not increased even more to allow fast and easy-reading results. The goal of this instance is to test the model, when more surgeries have to be scheduled, and more incompatible situations occur, like overlapped requests or requests not compatible with the MSS.

In **Figures 5.1** and **5.2**, are the resulting schedules, for equal weight values, for the first and second toy instances, respectively. These final schedules, never include overlapped surgeries, happening at the same time and room, and only schedule each surgery once, in open rooms. This means the model follows the first two constraints that ensure these events, for both toy instances. Also, each surgery is scheduled entirely in one day and room in both cases.

Due to dangerous transportation of the material, there are certain surgical specialties that have to be scheduled in a specific room, while others can occur in any available room. This is imposed by constraints (4.7), and, in the instances, is translated by parameter ζ_{er}. With the information from **Tables**

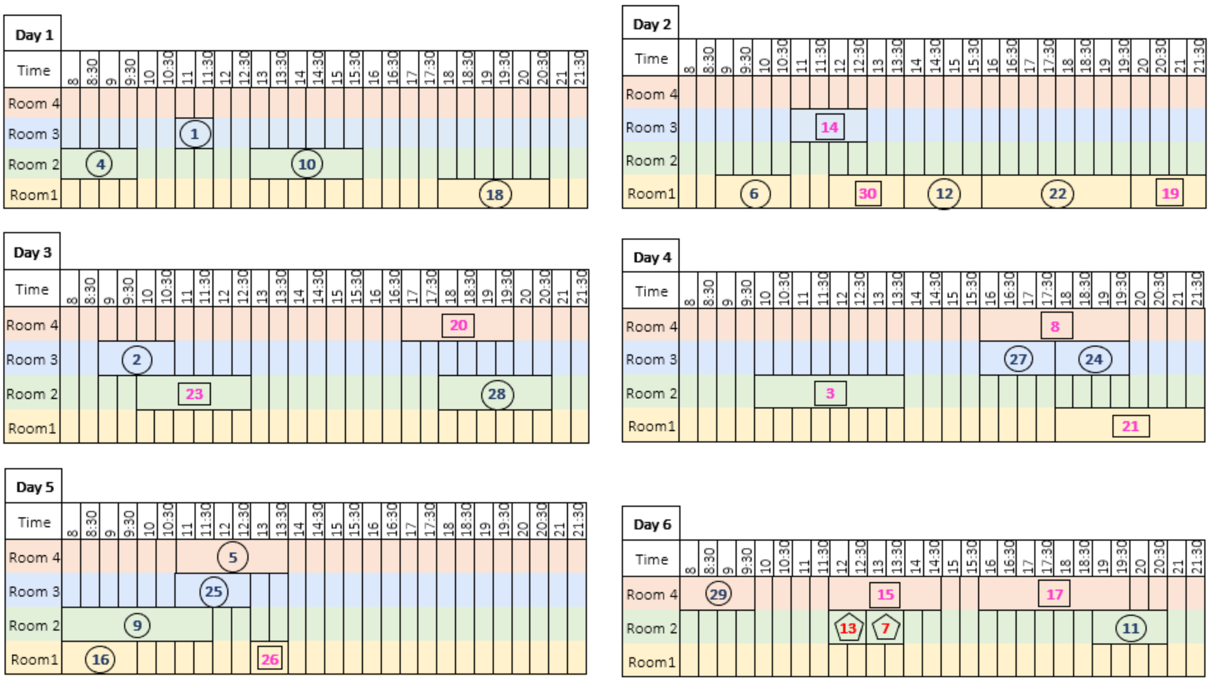

Figure 5.1: Final OR Schedule using the first toy instance, with weight values for third objective of: $k_1 = k_2 = 0.5$. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

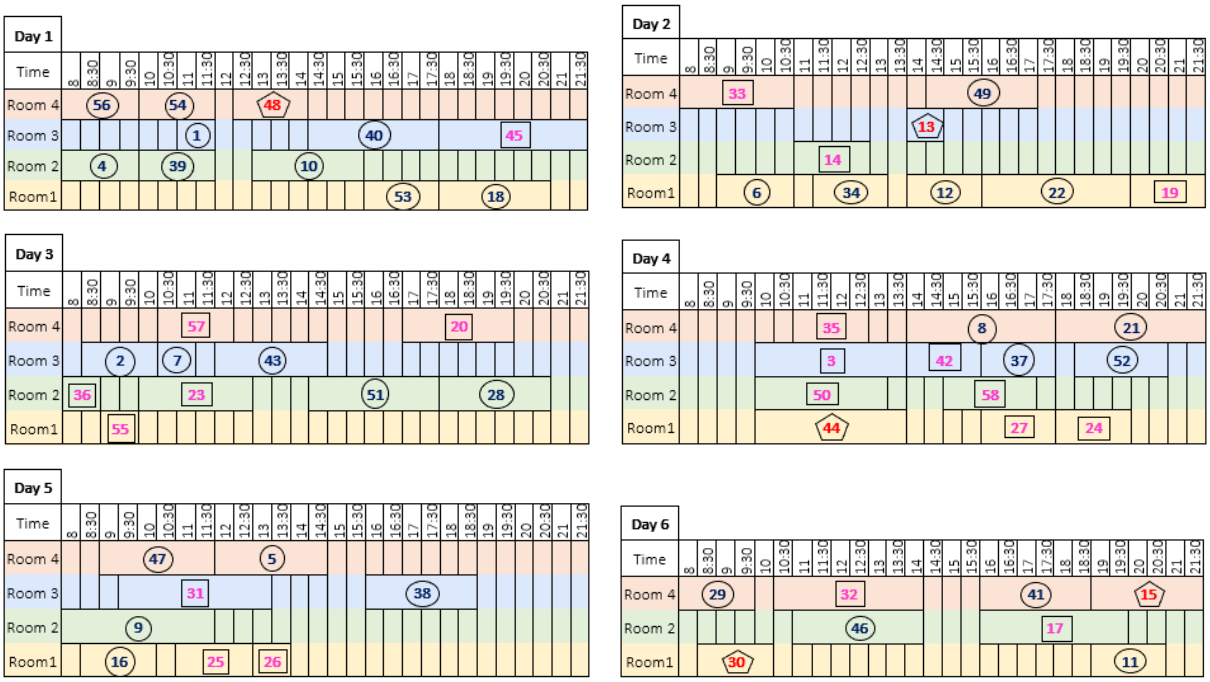

Figure 5.2: Final OR Schedule using the second toy instance, with weight values for third objective of: $k_1 = k_2 = 0.5$. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

5.3, A.1 and **A.2**, the surgeries that have a room restriction, in both toy instances, can be identified. First, Specialty 1 procedures can only be scheduled in Room 4, which is verified for Surgeries 5, 8, 15, 32, 41, 47, 48, 54 and 56, the ones belonging to this specialty. The surgeries from Specialties 2 and 9, namely, Surgeries 6, 12, 16, 18, 19, 22, 26, 30, 34, 44 and 53, can only be scheduled in Room 1. Again, in **Figures 5.1** and **5.2**, that can be observed. Finally, Surgeries 4, 9, 10, 23, 28, 39 and 51, that correspond to Specialties 5 and 6, have to be scheduled in Room 2, which they are in fact. The remaining surgeries can be assigned to any room, it what concerns this constraint. It is verified that the model follows constraints (4.7).

The start of each surgery corresponds to the first timeslot the surgery occupies, and it occupies only the timeslots correspondent to its duration estimate. No surgery is scheduled to start in a timeslot, for which there is not enough following slots to allow the surgery to end, before the OR closes.

Concerning the staff, the scheduled surgeon for each surgery corresponds to the responsible surgeon that sent the surgical proposal, which can be verified in the surgeon's schedules, presented in **Figures 5.3** and **5.4**, for the first and second toy instances, respectively. In **Figures 5.5** and **5.6**, the staff schedules can be observed, again for the two toy instances, and confirmed that only one anesthesiologist and two nurses are assigned for each surgery. The final schedules for the surgeries are compatible with the nurses, anesthesiologists and surgeon schedules and all staff members, are assigned only one surgery simultaneously, for both toy instances.

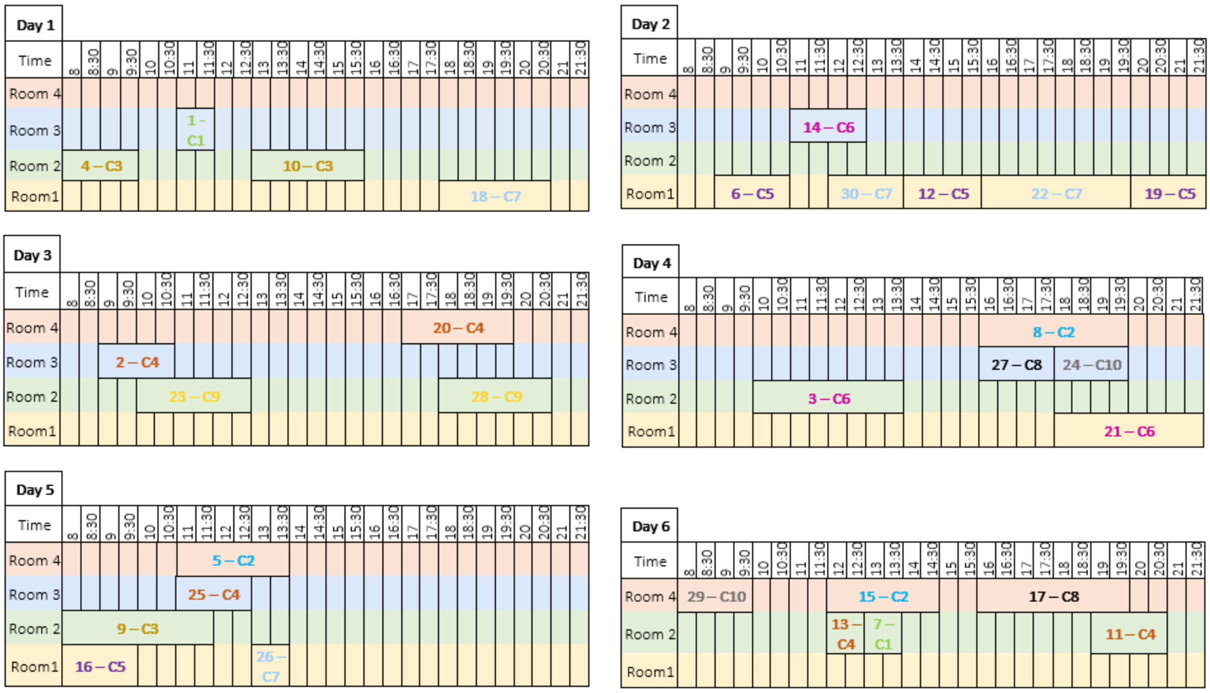

Figure 5.3: Final Surgeon Schedule using the first toy instance, with weight values for third objective of: $k_1 = k_2 = 0.5$. Each surgeon is identified with a different color.

In terms of objectives, for the first toy instance, in **Figure 5.1**, the first two objectives, are easily maximized. Specifically, for objective (4.1), the maximization of the number of surgeries scheduled, all the surgeries are always scheduled since, in this instance, the set S is relatively small. As all 30 surgeries are scheduled, the resulting profit, related to objective (4.2), is the sum of the profit of all

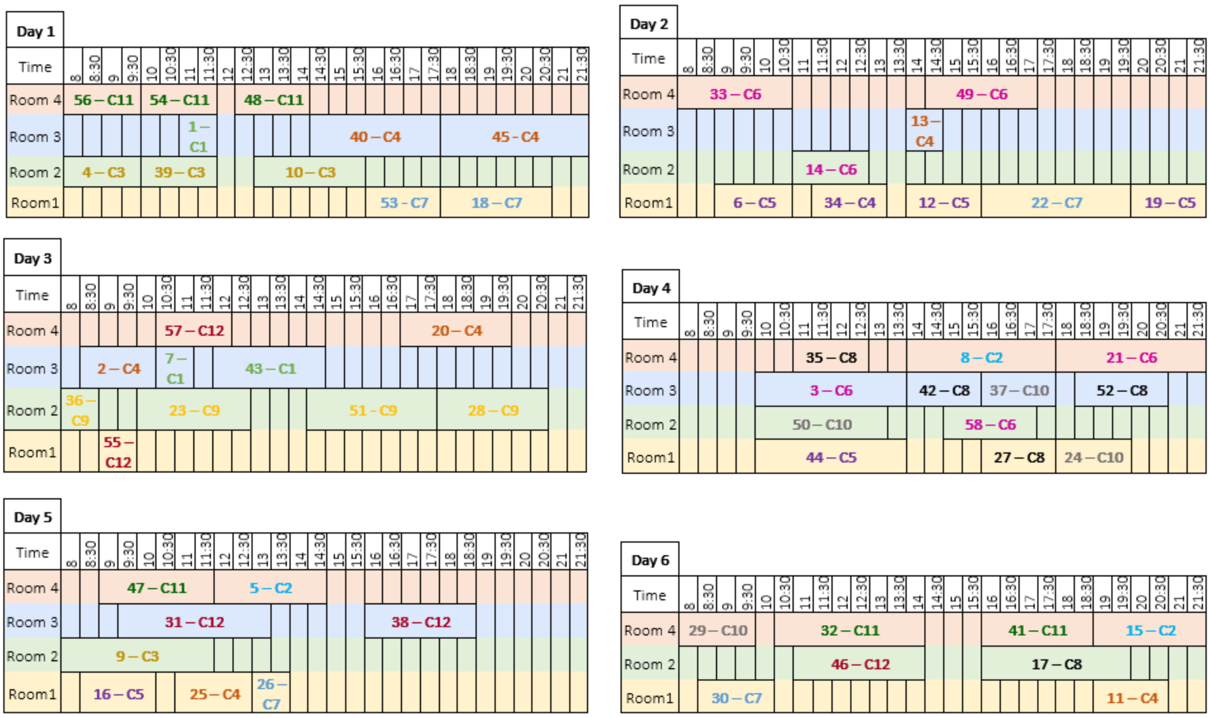

Figure 5.4: Final Surgeon Schedule using the second toy instance, with weight values for third objective of: k_1 = k_2 = 0.5. Each surgeon is identified with a different color.

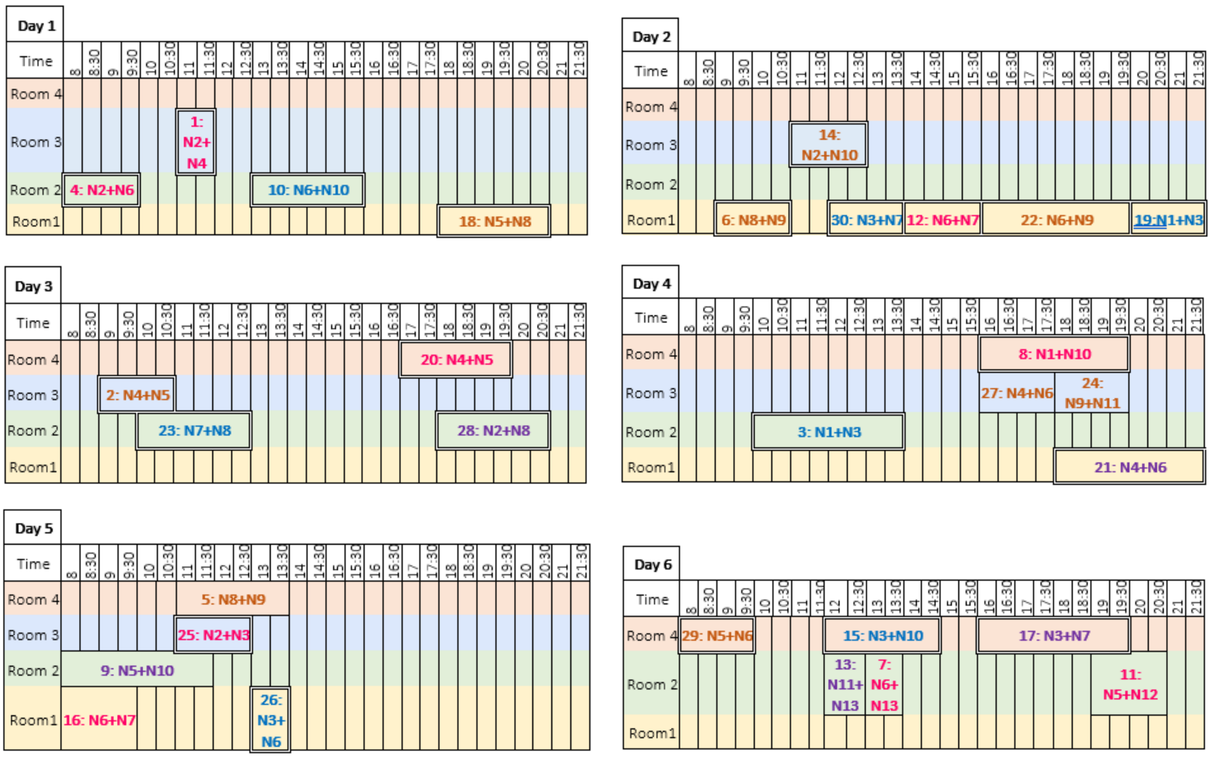

Figure 5.5: Final Anesthesiologist and Nurses Schedule using the first toy instance, with weight values for third objective of: k_1 = k_2 = 0.5. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

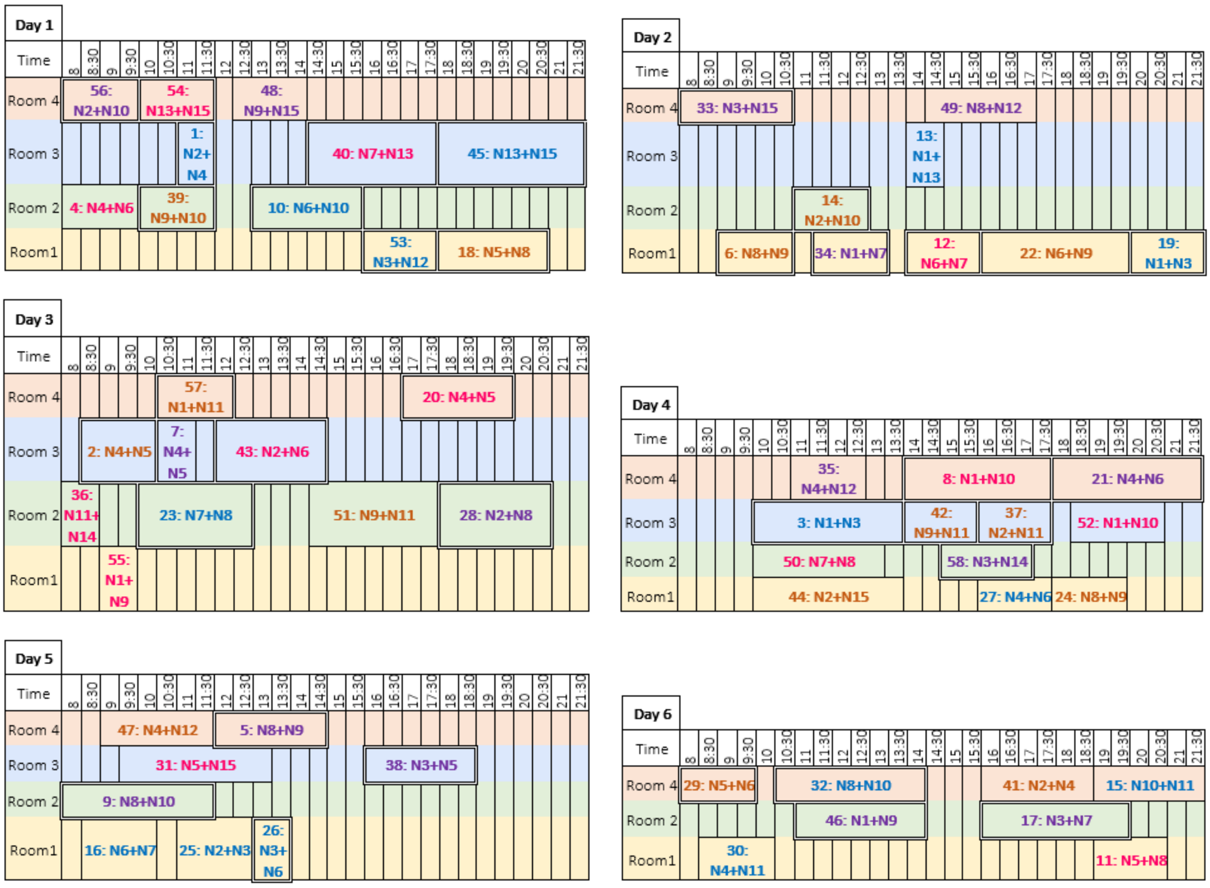

Figure 5.6: Final Anesthesiologist and Nurses Schedule using the second toy instance, with weight values for third objective of: $k_1 = k_2 = 0.5$. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

the surgeries of the sample, being also easily maximized. Although the second toy instance has an increased dimension, maximizing the objectives (4.1) and (4.2) remains easy. The 58 surgeries of the set can all be scheduled, so both the number of surgeries and the profit are maximized in **Figure 5.2**.

Concerning the third objective, in **Figure 5.1** can be easily observed, that no surgery is scheduled without respecting at least the MSS or the surgeon's request. Most of the surgeries can be scheduled respecting both, since the request is compatible with the MSS. For the cases in which this does not happen, most surgeries are scheduled according to the surgeon's preferences, but it can be considered that a balance does exist. Since this instance is small sized, it becomes easy to follow the surgeon's request because the final schedule is not full. For the second toy instance, in **Figure 5.2**, it can be seen that a balance between surgeries scheduled according to the MSS or surgeon's preferences is also achieved. However, for a higher number of surgeries, new types of scheduling situations appear.

The objective is calculated through a count of matching values between the final schedule, the α_{sdtr}, and the MSS (ν_{er}), or the surgeon's request (μ_{sdt}, μ_{asdt}, μ_{nsdt}). Therefore, if a surgery is scheduled occupying, in half of its duration, the timeslots asked by the surgeon, and, in the other half, the MSS shift in which the surgery must be scheduled, it can be considered that the surgery is scheduled according to both, and a balance is reached this way.

An example of this situation is Surgery 8 (Specialty 1), in **Figure 5.2**, which is schedule for Day 4, in Room 4, at 2p.m., occupying 8 timeslots. In the first 4 timeslots, in the morning shift, the surgery is respecting the MSS, but is not scheduled for when the surgeon requested. On the other hand, in the last 4 timeslots, since it is occupying the afternoon shift, it does not respect the MSS anymore, but it is occupying half of the timeslots requested. The surgeon had requested the surgery to be scheduled for Thursday, Day 4, at 4p.m. Other types of this balance are found, namely for Surgeries 40, 49 and 51. For these, it is also considered they respected both MSS and surgeon's request.

Another new situation is represented in **Figure 5.2**, for Surgeries 16 and 53, which are both scheduled according to the MSS. However, the hour in which the two surgeries start, corresponds to 30 minutes later than requested, which is translated in one timeslot. This situation is classified as following both the MSS and the surgeon's preferences, since one timeslot is considered irrelevant. The other surgeries labeled in blue (circle) are the cases in which the surgery is completely scheduled according to the request, and respecting, in its full duration, the MSS.

Finally, one special situation is found. Surgery 3, scheduled for Day 4 at 10 a.m., occupying 8 timeslots, is not scheduled according to the MSS. Concerning the surgeon's request, the surgery respects it in half of its duration. However, it is considered that this surgery is scheduled following the surgeon's preferences since, the MSS is not taken into consideration at all, and it tries to match the surgeon's request. Additionally, in a real situation, if the difference between the requested hour and the hour the surgery is scheduled means the requested staff is available, it is most likely the surgeon would prefer the hour scheduled.

Concluding, it can be considered that a balance is presented in the final schedule, as the majority of the surgeries take into consideration, in some way, both the MSS and the surgeon's request. The increased size of the sample in the second toy instance causes different types of results, but the objectives are maximized.

The staff schedule has to be analyzed in terms of following the surgeon's request or not, since it is also considered in the third objective. Almost all surgeries are scheduled with the staff requested, as it can be observed in **Figures 5.5** and **5.6**. The surgeries in single line boxes are not performed by the entire team asked, however, in some cases, some members assigned are the ones asked and others are not. In cases like Surgeries 7 and 13, for the first toy instance, and 13 and 48, for the second, no member of the team assigned in the schedule is asked by the surgeon. The remaining surgeries in single line boxes, for both instances, have a mixed team, having members requested by the surgeon and others that are not. Since the second toy instance is bigger, and the staff capacity is the same as in the first, it becomes harder to follow the surgeon's request in the entire team. However, within the mixed team surgeries, in a significant number of them, only one of the team members is not requested by the surgeon. Therefore, the surgeon's request is not ignored, and it is indeed maximized.

The relevant analysis is the difference in the schedule when the weights vary, especially for the surgeries scheduled only respecting the MSS or only respecting the surgeon's request. With that in mind, in **Figures 5.7** and **5.8**, is the final schedule with weights k_1 = 1 and k_2 = 0, for the first and second toy instances, respectively. **Figures 5.9** and **5.10**, present, for the first and second toy instances, respectively, the staff schedule, with the same weight values.

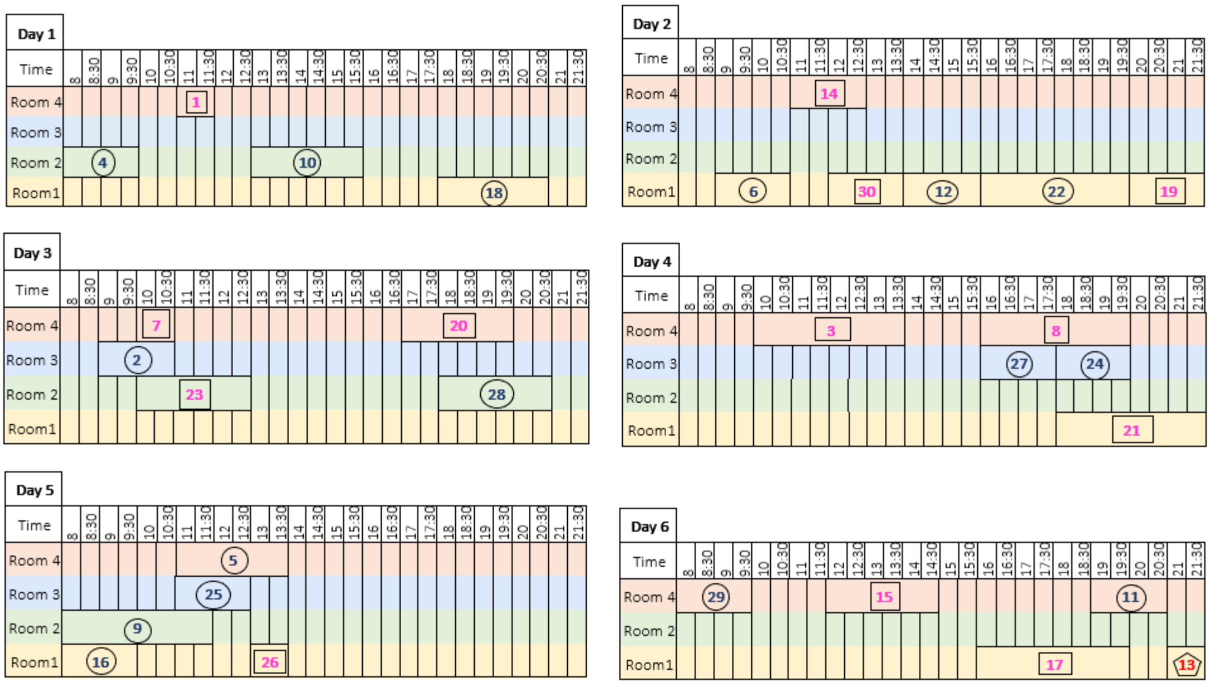

Figure 5.7: Final OR Schedule using the first toy instance, with weight values for third objective of: k_1 = 1 k_2 = 0. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

For the first toy instance, it can be observed a decrease, not significant, in the surgeries scheduled respecting the MSS in general, from 19, in **Figure 5.1**, to 17 in **Figure 5.7**. However, since most surgeries respect both MSS and the surgeon's request, the ones that keep following the MSS in **Figure 5.7**, probably result from a coincidence. Since the request is compatible with the MSS, even if the model ignores the MSS, but respects the surgeon's request, it can still result in matching the MSS. For the second toy instance, in **Figure 5.8**, the number of surgeries scheduled only respecting the surgeon's preferences, increases significantly, to a total of 39 surgeries, comparing to the 21 in **Figure 5.2**. The surgeries scheduled only respecting the MSS decreases from 5, for equal weights, to 2 surgeries. For this instance, some special cases have to be detailed, since some assumptions are made.

For the cases in which the MSS is respected and the request is only neglected in a maximum of two timeslots, the surgery is considered to take into consideration both the MSS and the surgeon's preferences. This is the case of Surgeries 5 and 10 in **Figure 5.8**. For the cases in which the MSS is ignored, and the request is only respected in at least half of the surgery duration, the surgeries are classified in pink (square), as Surgeries 3 and 32 are. In this situation, it is considered that only the surgeon's preferences are maximized, that is why the surgeries are classified this way.

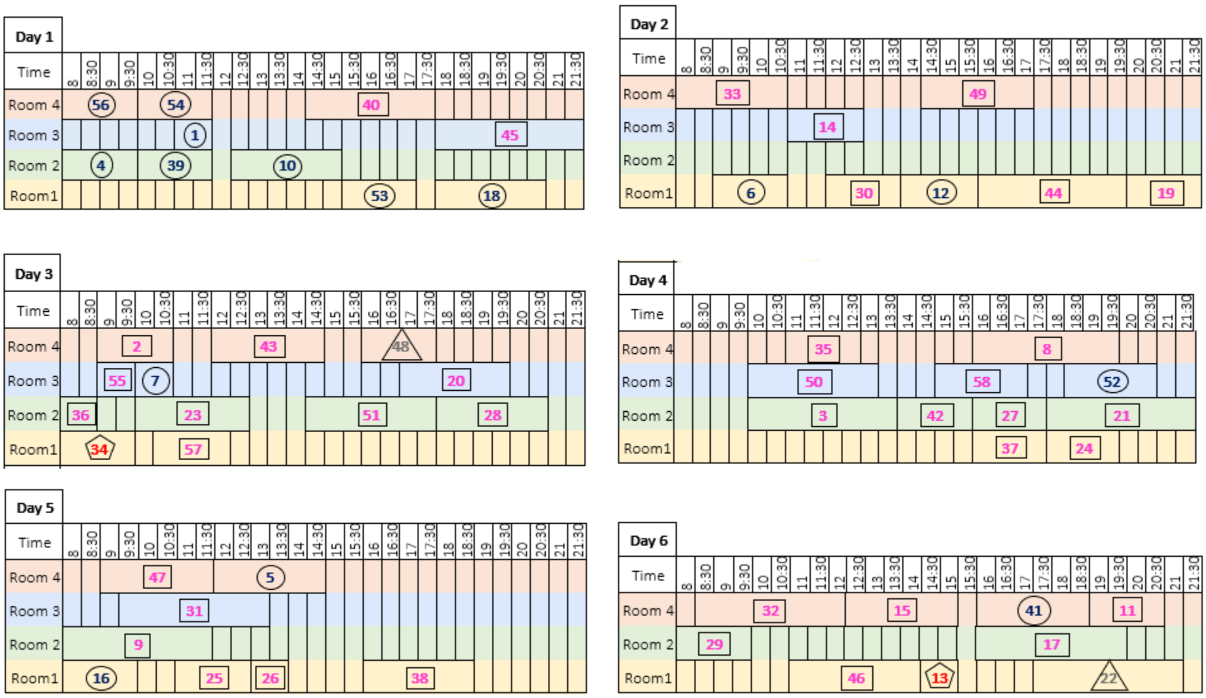

Figure 5.8: Final OR Schedule using the second toy instance, with weight values for third objective of: k_1 = 1 k_2 = 0. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS; Gray/Triangle - surgeries scheduled without respecting either.

For the surgeries respecting the surgeon's request, but occupying both morning and afternoon shifts, and, for that reason, only partially respecting the MSS, a rule is established to classify the surgeries. The ones occupying at most one timeslot in the shift in which the surgery is not allowed to be scheduled, are labeled in blue (circle), considering that respect both MSS and the request. On the other hand, the ones occupying more than one timeslot in the "wrong" shift, are labeled in pink (square), because it is considered that only the surgeon's request is taken into consideration.

A new situation appears in **Figure 5.8**. Surgeries 22 and 48 are scheduled without respecting the MSS nor the surgeon's request. This situation does not happen in the first toy instance, probably due to its size. In both cases, the day and hour requested are occupied by another surgery, and since both these surgeries belong to specialties with room restrictions, it becomes harder to fulfill the request.

In **Figures 5.9** and **5.10**, the majority of the surgical teams are chosen according to the surgeon's request. For the first toy instance, the number of surgeries that do not have the entire requested team, only decreases by one, comparing to **Figure 5.5**, and for the second instance, this number is the same as in **Figure 5.6**. The number of surgeries in which no team member is in the surgical proposal, is still 2, for both toy instances, the same as for equal weight values. The remaining have a mixed team, with some members requested by the surgeon. In the mixed teams there can be a higher match between the team scheduled and the request, however, it is not a relevant number for the first toy instance. On the other hand, for the second, in the 22 surgeries in single line boxes, the surgeon's preferences are highly considered, since in 13 surgeries, only one of the team members asked is missing. In these situations

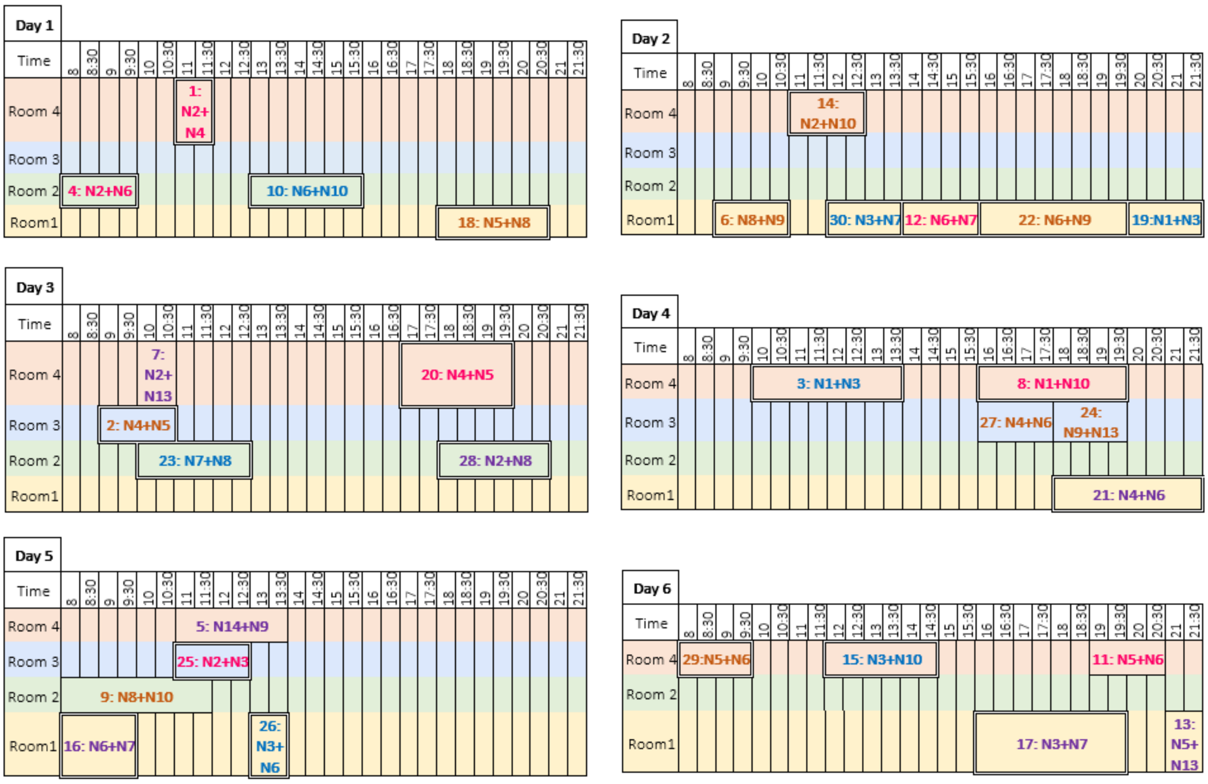

Figure 5.9: Final Anesthesiologist and Nurses Schedule using the first toy instance, with weight values for third objective of: k_1 = 1 and k_2 = 0. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

the surgeon's request is not entirely respected, but is clearly maximized. It can be concluded that the objective part that concerns the surgeon's preferences, associated with the weight k_1, is prioritized comparing to the part that concerns the MSS compliance, for both toy instances.

The same analysis is performed, for the first toy instance, for the weight values k_1 = 0 and k_2 = 1, displayed in **Figure 5.11**, which contains the resulting OR schedule, and in **Figure 5.13**, with the staff schedule. For the second toy instance, the analysis could not be performed with the intended weights, due to the limited CPU capacity of the machine in which the tests are performed. With that in mind, an analysis for the values k_1 = 0.05 and k_2 = 0.95 is presented, in which is still expected the MSS compliance to be highly prioritized, comparing to the surgeon's preferences. The resulting OR schedule for the second toy instance is in **Figure 5.12**, and the staff schedule in **Figure 5.14**.

The cases in which the surgery occupies at most two timeslots in the other shift, where another specialty should be scheduled, are considered to follow the MSS entirely. For the first toy instance, Surgeries 19 and 9 are scheduled in the morning and afternoon shifts simultaneously, but are classified as following the MSS. Surgery 9 is occupying two timeslots in the wrong MSS shift and Surgery 19 is occupying one. For the second toy instance, as considered before, in situations the MSS is respected and the surgeon's request is not met by one timeslot (equivalent to half an hour), the surgery is considered to follow both, as it can be observed, in **Figure 5.12**, for Surgeries 17, 47 and 53. If the difference between

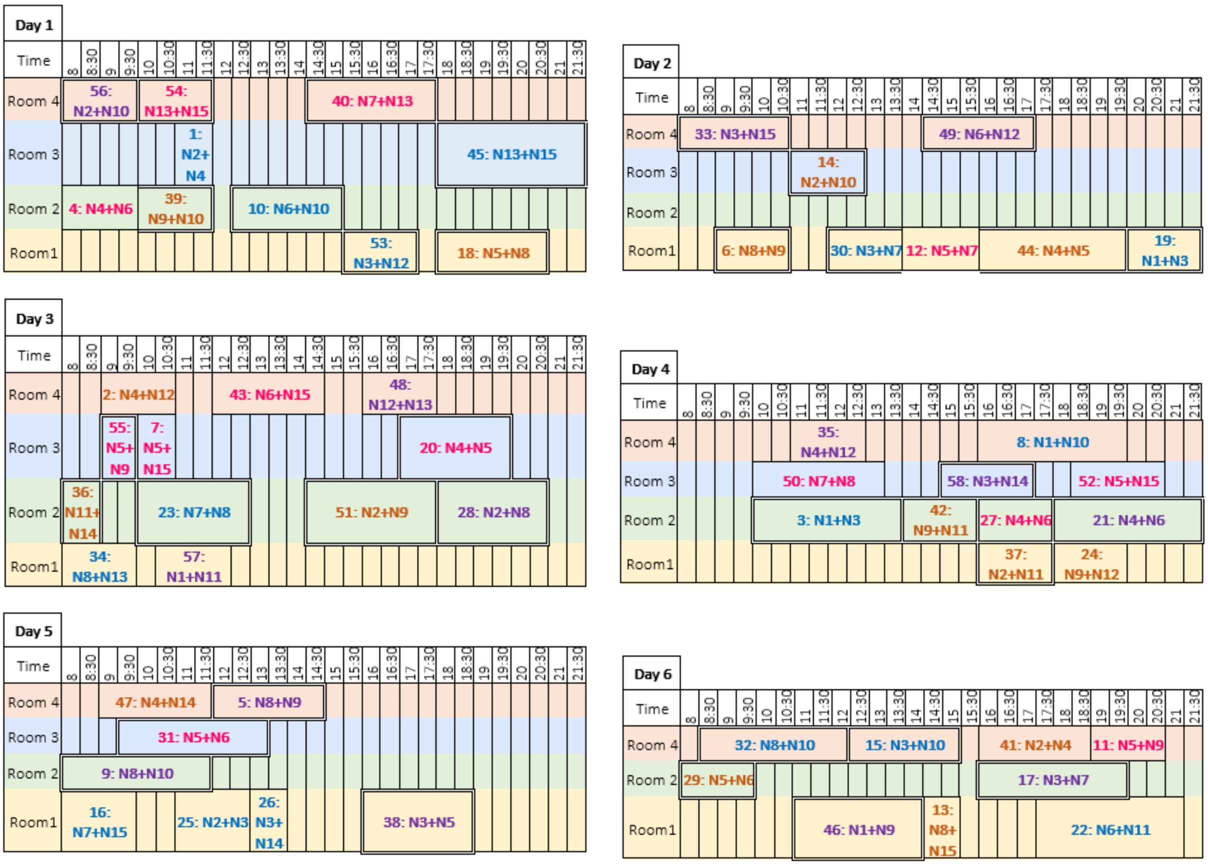

Figure 5.10: Final Anesthesiologist and Nurses Schedule using the second toy instance, with weight values for third objective of: k_1 = 1 and k_2 = 0. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

the schedule and the request is more than two timeslots, the surgery is considered to only follow the MSS, which is the case of Surgeries 40 and 49.

For these weight values, it is clear that the surgeon's preferences are not taken into consideration, as the entire schedule for the first instance (**Figure 5.11**) only respects the MSS. For the second (**Figure 5.12**), there is no surgery scheduled without following the MSS, and the ones scheduled also according with the surgeon's request are adjusted to the MSS. Even though the analysis performed, for the second toy instance, did not correspond to the intended weight values, the results indicate a clear shift when compared to the other weight values presented before.

The staff schedules in **Figures 5.13** and **5.14**, are also clear indicators of how the surgeon's preferences are ignored for these weight values. In no case, the team assigned corresponds entirely to the team requested by the surgeon, for the first toy instance, and, for the second, this number decreases from 36 of the previous analyses, to 24. However, for the first toy instance, coincidental or not, there are a total of 14 cases in which the team is mixed, having members requested and others not, which represents almost half of the sample. In 12 of these cases, only one member of the assigned team is requested by the surgeon. In the second toy instance, from the 34 surgeries in single line boxes, 17 are scheduled with an entire not requested team, and 9 with a team only including one member requested

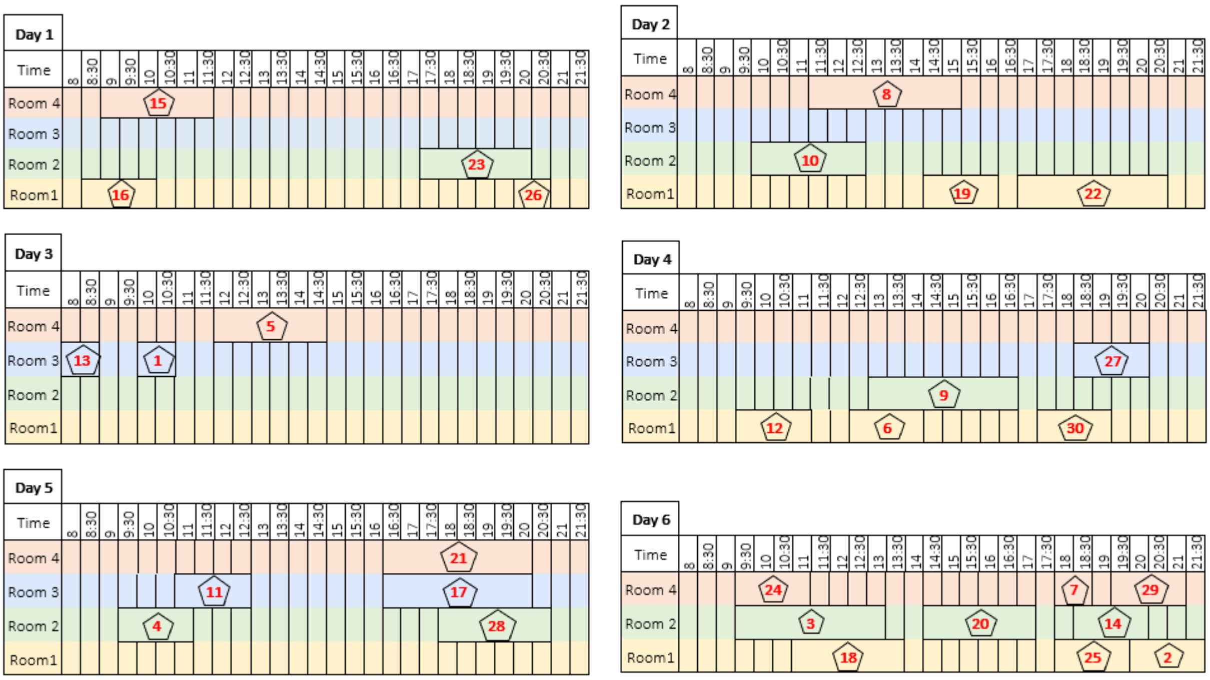

Figure 5.11: Final OR Schedule using the first toy instance, with weight values for third objective of: k_1 = 0 k_2 = 1. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

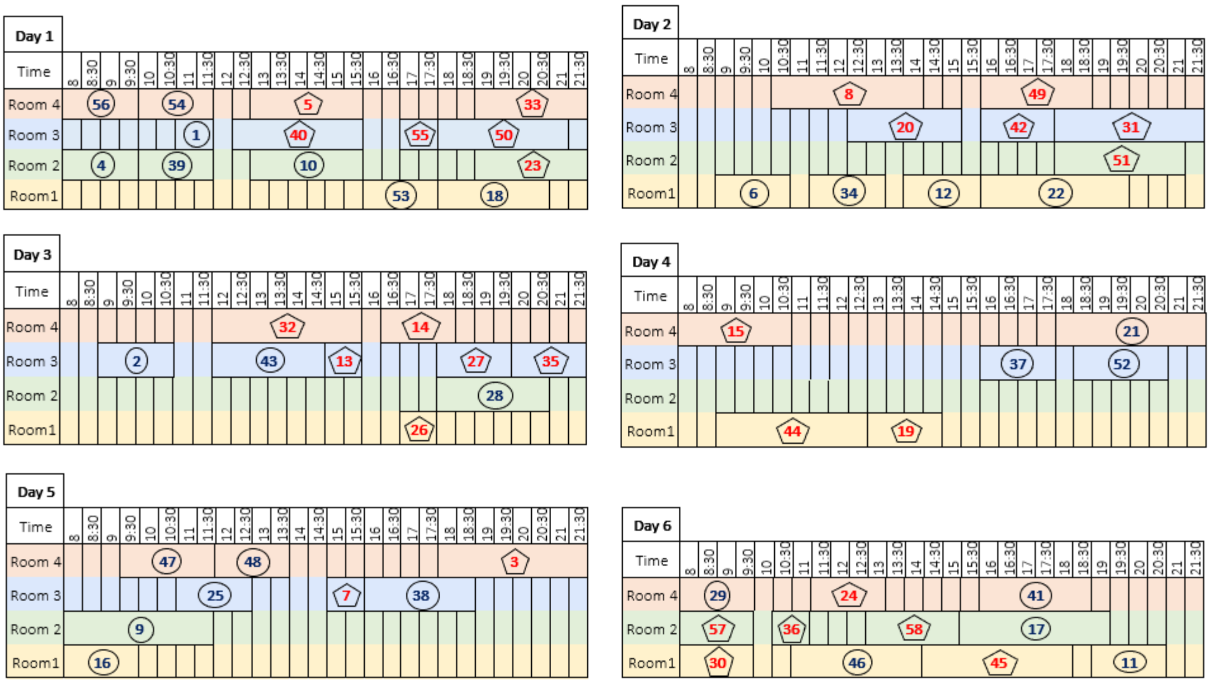

Figure 5.12: Final OR Schedule using the second toy instance, with weight values for third objective of: k_1 = 0.05 k_2 = 0.95. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS.

by the surgeon. The surgeon's preferences team-wise are visibly neglected, more evidently for the second toy instance, and in terms of day and hour, the MSS is clearly prioritized, since there is no case of a

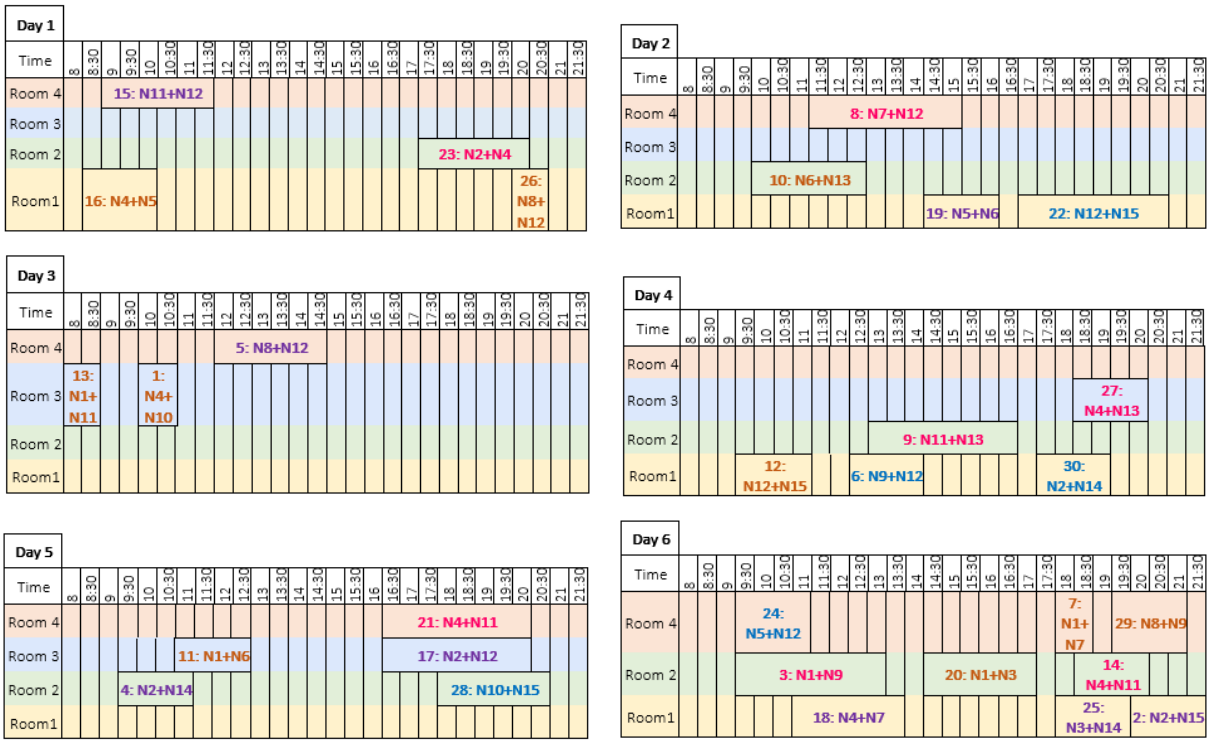

Figure 5.13: Final Anesthesiologist and Nurses Schedule using the first toy instance, with weight values for third objective of: k_1 = 0 and k_2 = 1. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

surgery scheduled only considering the surgeon's request. Overall, considering the variation of weights for the third objective, 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 for each surgery.

On the other hand, when the values are switched, now being k_1 equal to 1 and k_2 0, the final schedule is completely different. Almost all the surgeries in the instance 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 followed, along with time and day preferences. 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. There are surgeries being scheduled respecting the hour and day asked by the surgeon, as well as nursing team and anesthesiologist, and simultaneously the hour and room imposed by the MSS. Others are only scheduled according to the surgeon's request, ignoring the MSS compliance, and still, others, are scheduled according to the MSS, ignoring the surgeon's preferences. It can be considered the model balances well both parts of this objective, as it is intended.

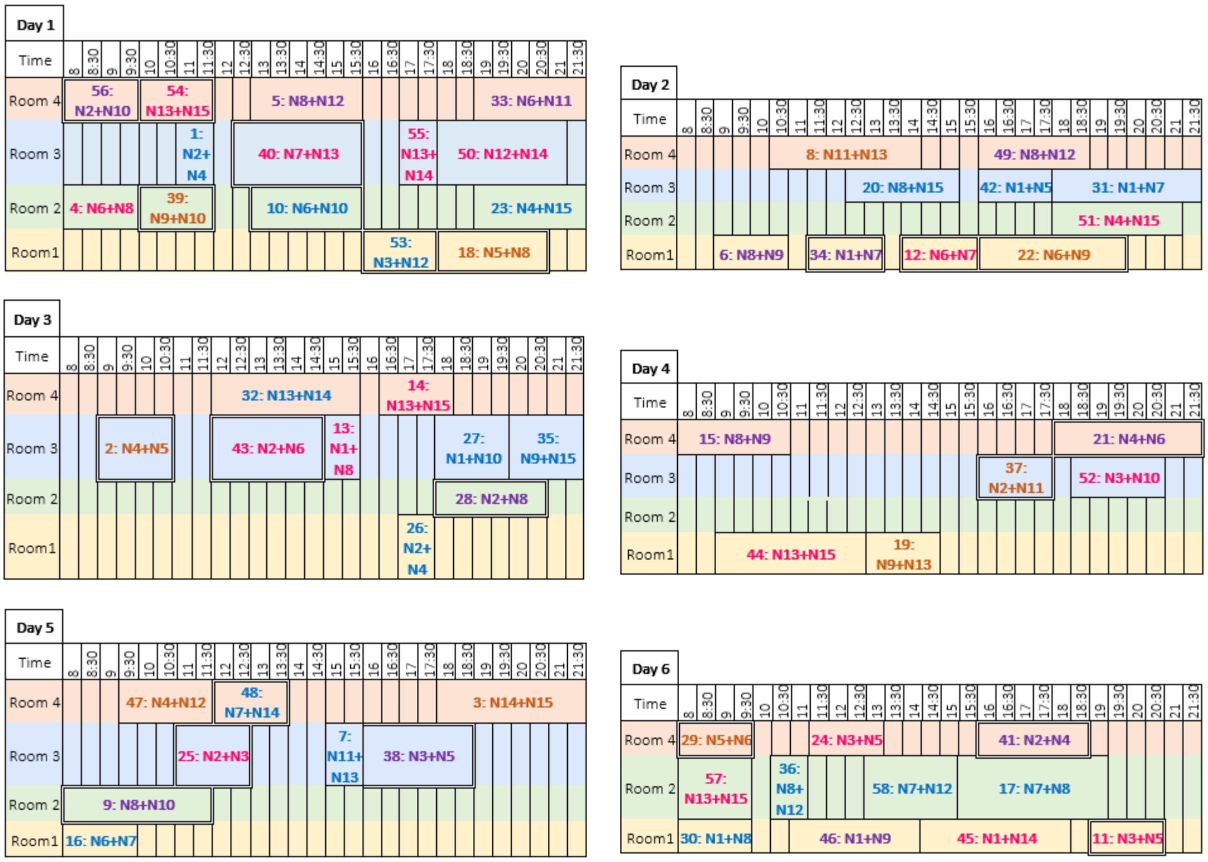

Figure 5.14: Final Anesthesiologist and Nurses Schedule using the second toy instance, with weight values for third objective of: k_1 = 0.05 and k_2 = 0.95. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgeries in double boxes are scheduled with the entire staff requested by the surgeon.

5.3 Chapter Conclusions

This chapter presents the technical model validation performed, detailing first the instances used, and, afterwards, the results associated with those instances.

The model is tested using two toy instances, for which the main difference is the instances dimension, as the second contains approximately twice the number of surgeries to schedule than the first. The results of these numerical tests are satisfactory, since the model achieves feasible solutions in useful time. The weight variation analysis for the third objective also presents the expected behavior for the model, as the results change according to the weight values assigned.

The next chapter presents a test perfomed using real data collected from the hospital, and a comparison between the results and the current situation of the case study. In addition, a validation by the main stakeholder is also present in **Chapter 6**, in which the work done is explained and the solutions presented. The results are discussed with the stakeholder and managerial insights are inferred.

Chapter 6

Results and Hospital Validation

In this chapter, the instance created, based on real data from the hospital, is firstly described and the results using that real instance are then discussed, in **Section 6.1**. Afterwards, in **Section 6.2**, the validation from the hospital's stakeholder is presented, and managerial insights resulting from the feedback received are detailed.

The goal of this chapter is to obtain results using real information, to analyze these results and compare them with the current scheduling strategy of the case study hospital. Obtaining feedback from the hospital's main stakeholder, allows managerial insights concerning the OR current management strategy and possible changes to implement.

6.1 Results using Real Instance

A real instance is built, using data from an entire week, collected from the hospital. The goal is to produce real results and compare them with the real schedule for the same week.

6.1.1 Instance Description

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. The final schedule built by the department for that week is also collected, for further comparison with the results. For privacy purposes, each surgery and staff member is assigned an ID number, the week in study is not revealed and the real schedule is transformed into a schedule similar to the results presented.

When the hospital's data is collected, some adaptations and assumptions must be done to allow

Table 6.1: Parameters considered for the Hospital Instance.

Parameter	Value	Details
$\|S\|$	46	Number of surgeries to be schedule. 36 of them needing a postoperative bed.
$\|C\|$	22	Number of surgeons responsible for the surgeries.
$\|D\|$	6	Number of days to schedule the surgeries. A weekly schedule is considered, from Monday until Saturday.
$\|A\|$	4	Number of anesthesiologists available.
$\|N\|$	15	Number of nurses available to scrub in the surgeries.
$\|R\|$	4	Number of operating rooms open to schedule the surgeries.
$\|E\|$	10	Number of surgical specialties correspondent to the surgeries to schedule.
$\|T\|$	28	Number of daily timeslots available to schedule the surgeries. This parameter is calculated considering the OR opens at 8a.m. and closes at 10p.m., and the timeslot time interval is 30 minutes.
nn	2	Number of nurses needed to assist a surgery.
ba	20	Number of beds available in the postoperative care.

the model's application to this data. In **Table 6.1**, the parameters with a single value are displayed. The number of anesthesiologists is adapted, since these professionals have a schedule of their own, including their days off. Therefore, throughout the week, the available anesthesiologists are not always the same. However, 4 anesthesiologists are always available, so the model remains with the set of anesthesiologists as it is presented so far, with a constant number of anesthesiologists. Moreover, the only number of nurses available is the total number of nurses in the entire surgical service team, which is 30 nurses. However, these are not all scrub nurses, i.e., not all the 30 nurses participate in surgeries. Additionally, since only 80% of this team is actually working, as mentioned in **Chapter 2**, it is estimated that the number of available nurses to participate in surgeries is 15. In addition, similarly to the anesthesiologists, the nurses are not the same everyday, but a constant number of available nurses is maintained throughout the week. Concerning the rooms, there are 4 available, OR3, OR4, OR5 and OR6. These are assigned a sequential ID number, from 1 to 4, in the order presented (OR3 - Room 1, OR4 - Room 2, OR5 - Room 3 and OR6 - Room 4).

Only the surgical specialties, associated with the surgeries in this instance, are included in the set of specialties. The remaining existent surgical specialties are omitted, since it is useless information. In the MSS implemented in the hospital, in **Table 2.1**, the Vascular Surgery and Angiographic Procedures are distinguished surgical specialties, with different time blocks assigned. In this test, these are considered grouped in one specialty, since when the specialty is indicated in the data, there is no difference between the two.

Concerning the specialties that have to be scheduled in a specific room, due to material that can not be transported, the situations considered are the following. Cardio-thoracic and Angiographic access procedures have to always take place in OR3. Orthopedic surgeries need to be scheduled in OR4 and, mainly due to the laparoscopic material availability, General surgeries are scheduled in OR6. The remaining surgical specialties are allowed to be scheduled in all available rooms. The designation of each specialty, together with the parameter ζ_{er}, that translates the fixed materials constraints, are detailed in

Table 6.2: Parameter ζ_{er} for the Hospital Instance

Specialty\Room	*1*	*2*	*3*	*4*	**Correspondent Specialty**
1	✗	✗	✗	✓	General
2	✓	✗	✗	✗	Cardio-thoracic
3	✓	✓	✓	✓	Ophthalmology
4	✓	✗	✗	✗	Vascular/Angiographic Procedures
5	✗	✓	✗	✗	Orthopedic
6	✓	✓	✓	✓	Urology
7	✓	✓	✓	✓	Otolaryngology
8	✓	✓	✓	✓	Plastic
9	✓	✓	✓	✓	Neurological
10	✓	✓	✓	✓	Rheumatology

✓ - specialty can be scheduled in room; ✗ - otherwise

Table 6.3: Parameter σ_{dr} for the Hospital Instance

Day\Room	*1(OR3)*	*2(OR4)*	*3(OR5)*	*4(OR6)*
1	OPEN	OPEN	OPEN	OPEN
2	OPEN	OPEN	OPEN	OPEN
3	OPEN	OPEN	OPEN	OPEN
4	OPEN	OPEN	OPEN	OPEN
5	OPEN	OPEN	OPEN	OPEN
6	OPEN	OPEN	CLOSED	OPEN

Table 6.2. One of the weekly operating rooms is closed on weekends, specifically on Saturdays. Since only OR2/3 and OR6 are included in the Saturday's MSS, one other room is randomly chosen to be open. In this case, OR4 is chosen to be open on Saturday, which is expressed by parameter σ_{dr}, in **Table 6.3**.

The MSS displayed in **Table 6.4** is based on the one used in the hospital (**Table 2.1**), and adapted to the instance. The morning shift is considered from the opening hour, 8a.m., until 4p.m., while the afternoon shift starts at 4p.m., until the OR closes, at 10p.m. In the shifts without a specialty assigned, all surgical specialties can be scheduled. It is not possible to distinguish the so called "External" surgeons, so these have to be scheduled without differentiating them from the remaining. In the special case of Orthopedic Surgery, for which there is an assigned shift in the MSS only for the external surgeons, the MSS has to be adapted. The external and internal surgeons are treated as equal, so both can operate in either one of the two shifts for Orthopedic Surgery. In the "Other Specialties" group are included for this instance: Neurological Surgery, Plastic Surgery and Rheumatology. Parameter θ_{se} connects each surgery with its surgical specialty. Due to its extension, **Table A.5**, containing this parameter, is included in **Appendix A**.

An issue encountered when collecting the data is that, most surgeons do not entirely fill the surgical proposal. Furthermore, none of them fill out the part where they have to specify the surgical team. Thus, the surgeon's preferences 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

Table 6.4: Weekly Master Surgery Schedule for the Hospital Instance.

	Week Days (Day 1 - Day 5)				Weekend (Day 6)	
	OR3	OR4	OR5	OR6	OR3	OR6
Morning shift	Specialties 2+3	Specialty 5	Specialty 4	Specialty 1	-	Specialty 7
Afternoon shift	Specialty 4	Specialty 5	Specialties 8+9+10	Specialty 6	Specialty 4	-

the surgeon's request. **Table A.6**, also in **Appendix A** due to its dimension, presents for each surgery, the estimated duration, d_s, the responsible surgeon, and the request from the surgeon in terms of day and hour. The duration presented in the table, and introduced in the model, corresponds to the one in the surgical proposal, with the turnover time added (30 minutes). The requests ”Not Available”, correspond to all the surgeries without a proposal available to the study. All the proposals from the specialty Ophthalmology are not available, and the remaining consist in isolated cases for which the proposal is not found. For this group of surgeries with absent proposals, nothing is introduced in parameter μ_{sdt}, translating an absence of the surgeon's request or preference. The profit margin for each procedure is not available and, therefore, not presented. Additionally, it is not included in the objectives when testing the model, with the real instance. Further analysis is presented, in **Section 6.1.2**, concerning its influence.

6.1.2 Results

First of all, it is important to assess the computational results, including gap and objective values achieved, present in **Table 6.5**. In this table are detailed, for the real instance, the total number of variables and constraints. In addition, for each test, the total running time, gap value, best bound, overall objective value and each objective values are also detailed in the table. The results concerning the OR schedule and staff schedule are then presented. Afterwards, a weight variation analysis is performed, without including the staff schedule, due to the absence of staff preferences in the surgeon's request.

Concerning the running times, an important note has to be taken. The more tests are performed in the same machine, in a short time interval, the slower it gets. This situation is even more evident in a machine with a capacity not ideal to run these type of models. With that in mind, the times may seem higher than preferred, but are considered satisfactory since all are close to one hour. In terms of gap values, the ideal null gap value is reached for every test made, which indicates an optimal solution is found.

As mentioned previously, the profit objective is not included, due to the unavailability of the information. In both toy instances, one smaller than the real, and the other bigger, in terms of number of surgeries to schedule, the profit maximization did not influence much the result. As it is inferred in **Chapter 5**, for this number of surgeries to schedule, the two first objectives are redundant. Since all

Table 6.5: Computational results for the Hospital Instance

	Weights		Hospital Instance	
	k_1	k_2		
Number of Variables	-		313 547	
Number of Constraints	-		56 318	
Running Time (sec.)	*0.5*	*0.5*	3155.77	
	1	*0*	4556.88	
	0	*1*	4153.52	
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	
Number of surgeries scheduled	*0.5*	*0.5*	46.0	
	1	*0*	46.0	
	0	*1*	46.0	
MSS vs. Surgeon's Preferences	*0.5*	*0.5*	82*k_1 150*k_2	116
	1	*0*	114*k_1 92*k_1	114
	0	*1*	5*k_1 152*k_2	152

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 its influence probably does not change the result. If available, the profit maximization would only cause all the surgeries to be scheduled, which is assured by the objective that maximizes the number of surgeries scheduled.

For the first objective, all surgeries are scheduled for all tests performed, leading to a maximization of the number of scheduled surgeries, as intended. Concerning objective (4.3), as concluded in **Chapter 5**, the values alone, do not provide relevant information to the analysis of this objective. Instead, the resulting schedules for each test are analyzed and compared, which allows more grounded conclusions about this objective. Also, since not all requests are available, the value of that part of the objective is naturally lower than the part concerning the MSS. Nevertheless, the values reached in the analysis with the weights k_1 = 1 and k_2 = 0, prioritize the surgeon's preferences, having a higher value associated, compared with the MSS value. For the analysis with the weights k_1 = 0 and k_2 = 1, the opposite situation is verified, and, in this case, the difference between values is even more evident. The first test performed is for the weight values k_1 = k_2 = 0.5, for which the results are presented in **Figures 6.1, 6.2** and **6.3**.

For equal weight values, a clear balance is achieved between following the MSS and the surgeon's request, which is shown in **Figure 6.1**. If a surgery only disrespects the MSS or the request by one timeslot, that situation is ignored and the surgery is classified as respecting it. This way, there is no

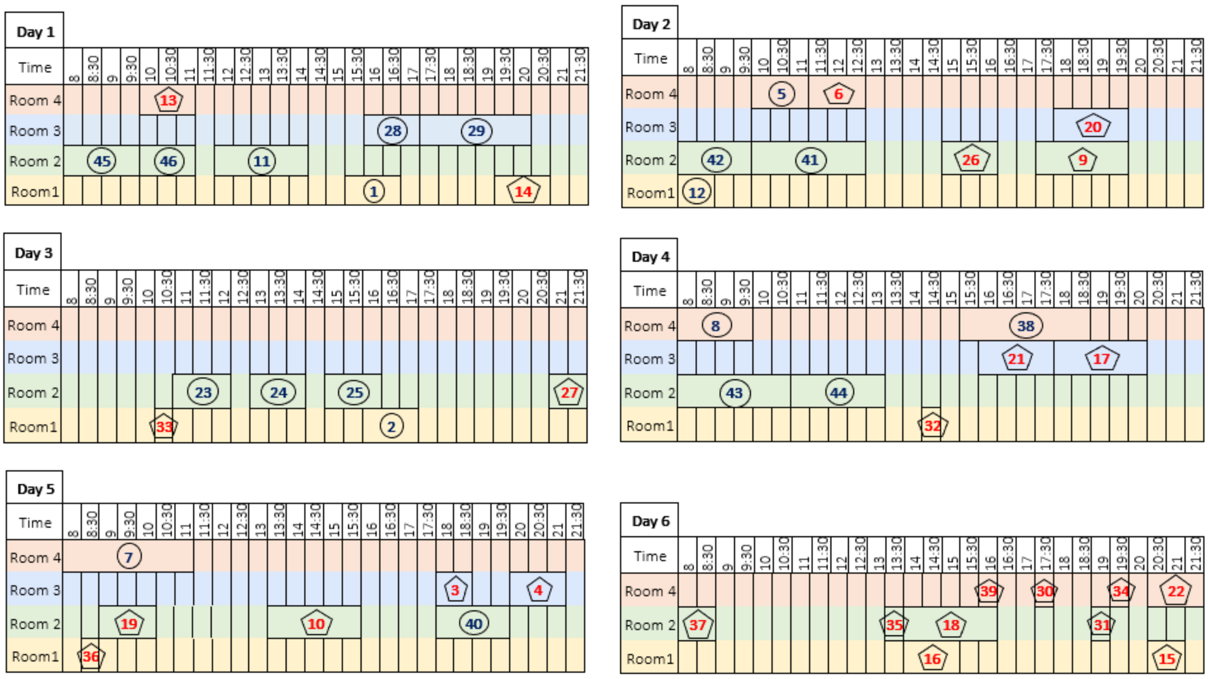

Figure 6.1: Final OR Schedule using the Hospital Instance, with weight values for third objective of: k_1 = k_2 = 0.5. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS; Gray/Triangle - surgeries scheduled without respecting either; Yellow/Arrow - surgeries with unknown request and that do not respect the MSS.

case of a surgery scheduled without respecting at least one of the options, the MSS or the surgeon request. All the surgeries for which the request is unavailable, are scheduled according to the MSS. An interesting aspect of this resulting schedule is the absence of surgeries scheduled only respecting the surgeon's preferences. However, if the requests made are compatible with the MSS, the best option is to respect both, which is the ideal solution for all surgeries.

Concerning the surgeon's schedule, it can be observed that each assigned surgeon matches the respective surgery's responsible surgeon, detailed in **Table A.6**. There is no situation of overlapped work for any surgeon. For presentation purposes, for the surgeries occupying only one timeslot, the nurses and surgeon assigned are not specified. Namely, for surgeries from number 30 to 36, in the surgeon's schedule (**Figure 6.2**), the surgeon is not detailed. However, those surgeries are identified with the same color, which corresponds to Surgeon 17. The same happens for Surgeries 30 to 36, and 39, for the nurses, which are not detailed, in **Figure 6.3**. The missing nursing teams for those surgeries, are displayed in **Table 6.6**. In terms of staff schedule, it is important to mention that for each surgery two nurses and an anesthesiologist are assigned, as expected. Additionally, there is no situations of overlapped surgeries for any staff member.

The weight variation analysis becomes relevant, specially to compare with the schedule built by the hospital, but also, to test the model's behavior for real data. In **Figure 6.4** is the resulting OR schedule for the weight values k_1 = 1 and k_2 =0.

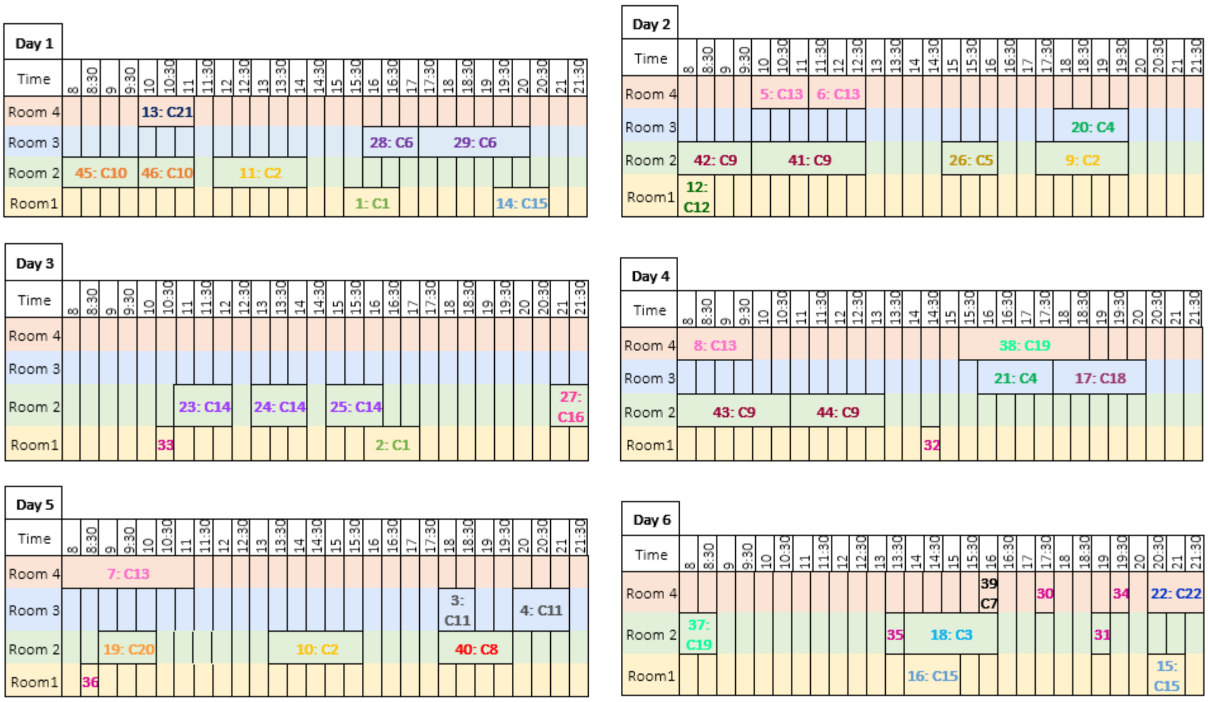

Figure 6.2: Final Surgeon Schedule using the Hospital Instance, with weight values for third objective of: k_1 = k_2 = 0.5. Each surgeon is identified with a different color.

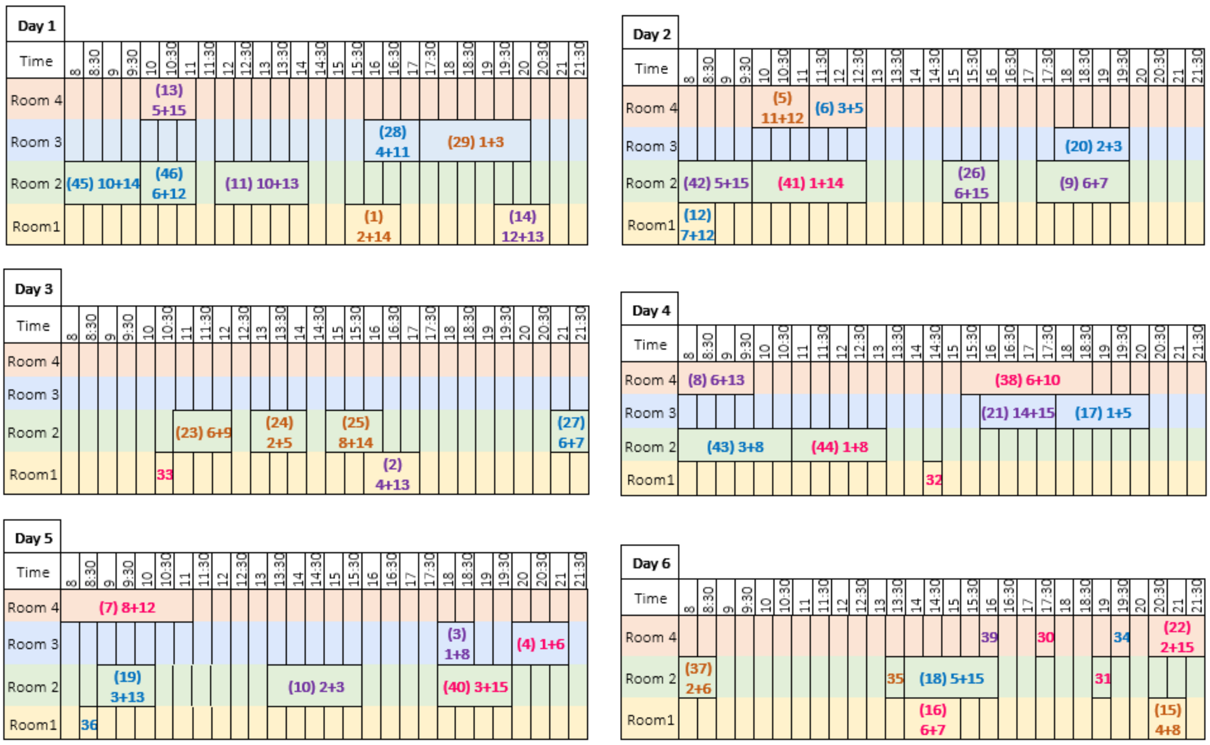

Figure 6.3: Final Anesthesiologist and Nurses Schedule using the Hospital Instance, with weight values for third objective of: k_1 = k_2 = 0.5. Each anesthesiologist is identified with a different color (Blue - Anesthesiologist 1; Pink - Anesthesiologist 2; Purple - Anesthesiologist 3; Orange - Anesthesiologist 4). The surgery IDs are between brackets and the nurses are identified by the two numbers ahead.

The surgeon's request can be considered prioritized in **Figure 6.4**. The cases in which the surgery is scheduled respecting both MSS and request may be coincidental, as the request matches the MSS. For

Table 6.6: Surgeries with the nurses absent in **Figure 6.3**, and correspondent nursing teams assigned.

Surgery	Nursing Team
30	N10 + N12
31	N11 + N12
32	N4 + N12
33	N11 + N12
34	N5 + N10
35	N2 + N9
36	N6 + N11
39	N1 + N13

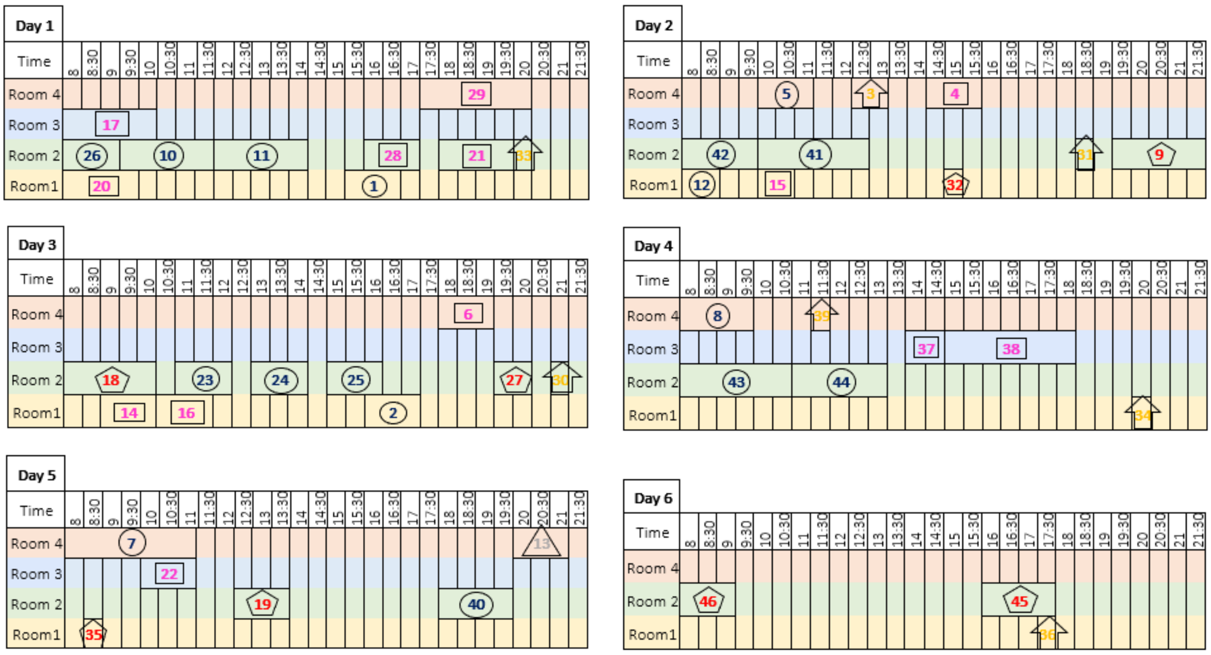

Figure 6.4: Final OR Schedule using the Hospital Instance, with weight values for third objective of: k_1 = 1 and k_2 = 0. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS; Gray/Triangle - surgeries scheduled without respecting either; Yellow/Arrow - surgeries with unknown request and that do not respect the MSS.

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 in **Figure 6.1**, 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 **Figure 6.5**, the result for the weight values k_1 = 0 and k_2 = 1, is displayed and the surgeon's requests are obviously ignored. From the objective values presented in **Table 6.5**, this is expected. 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. The maximum timeslots matching the request in a surgery correspond to less than half of the surgery's duration. Therefore, all surgeries are considered to be scheduled only respecting the MSS.

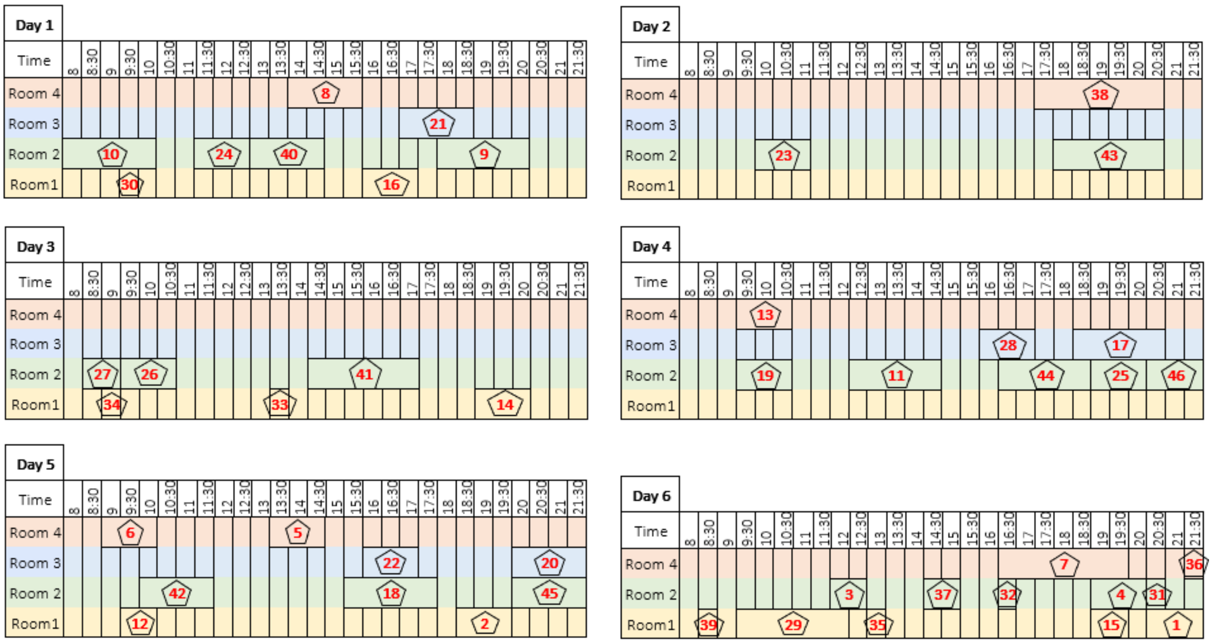

Figure 6.5: Final OR Schedule using the Hospital Instance, with weight values for third objective of: k_1 = 0 and k_2 = 1. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS; Gray/Triangle - surgeries scheduled without respecting either; Yellow/Arrow - surgeries with unknown request and that do not respect the MSS.

Comparison with Hospital Schedule

In **Figure 6.6**, the schedule built by the hospital, for the same week used to build the real instance, is presented for comparison. There is an evident difference between the model's results and the schedule built by the hospital, in the surgery durations. For unknown reasons, in some surgeries the hospital reserves smaller or bigger time blocks than the surgeon estimates. This could not be predicted to build the model, and no explanation is found for this difference, so it is considered irrelevant, since no conclusions can be made about this.

It can not 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. If all the surgeries can fit in the 5 weekly days, there is no need for the surgeons or the patients to have their surgeries on a Saturday.

Another aspect for which the hospital schedule can be considered better, is for the surgeries with unavailable requests. Specifically, for Surgeries 30 to 36, which have the same responsible surgeon, in the hospital schedule are all sequential. These surgeries are also scheduled according to the MSS. Additionally, probably the surgeon requested sequential timeslots, since the professionals usually prefer

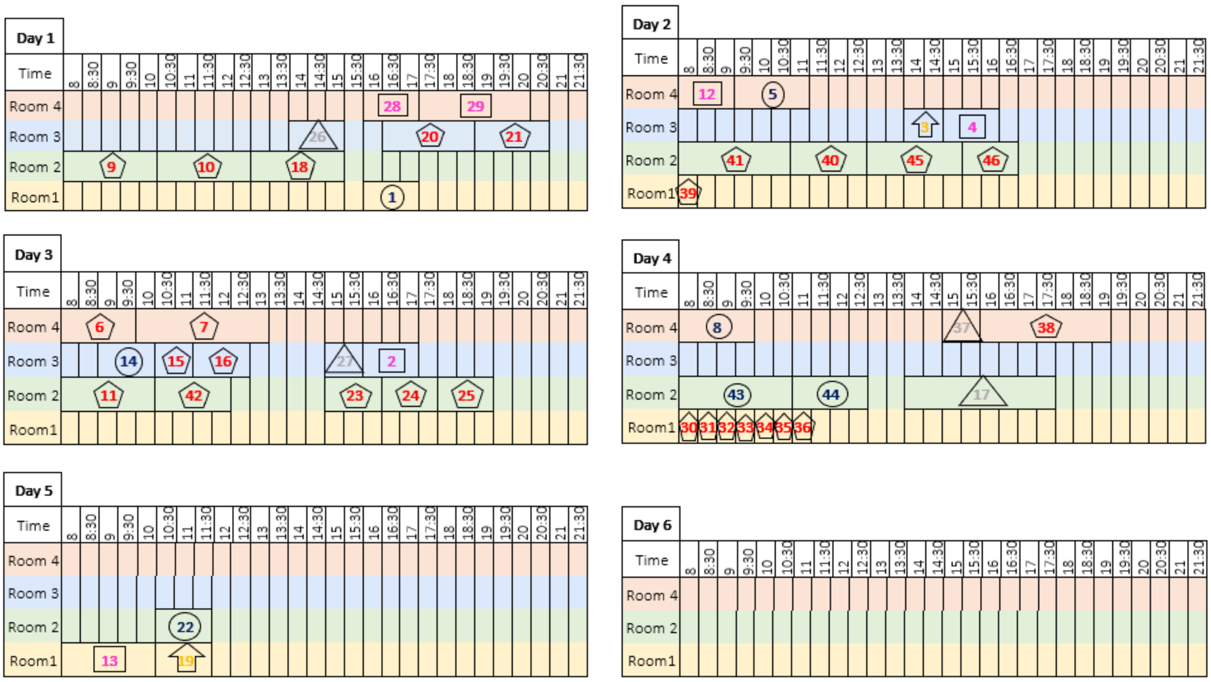

Figure 6.6: Hospital's Schedule for the same week as the Hospital Instance is related. Color/Shape code (ID numbers): Blue/Circle - surgeries scheduled respecting both MSS and surgeon's request; Pink/Square - surgeries scheduled only according to surgeon's request; Red/Pentagon - surgeries scheduled only respecting the MSS; Gray/Triangle - surgeries scheduled without respecting either; Yellow/Arrow - surgeries with unknown request and that do not respect the MSS.

to have their surgeries scheduled at least in the same day. However, without the requests available, for all resulting schedules, this group of surgeries is spread across the weekly days, which is not ideal. Of course the hospital had the requests available when building the schedule, so this comparison is not quite valid, and there is not much that can be done to improve the solution obtained by the model.

For the remaining surgeries, most of them do not match the surgical proposal, which confirms the existing issue in the hospital, when trying to integrate the MSS and the surgeon's preferences. Therefore, there is a probability of having unsatisfied staff, since the surgeon's usually like to have their requests attended. 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. The resulting schedule from **Figure 6.5** might not be the answer, since it ignores all the requests, and neither the one in **Figure 6.4**, that neglects the MSS, but maybe the schedule for the equal weight values analysis, from **Figure 6.1**, can be used.

6.2 Hospital Validation

This section aims at gathering the main stakeholder's feedback, concerning the results from **Section 6.1**. With that in mind, 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.

After the model's structure and components are clarified, the solutions obtained in **Section 6.1.2**, with the real instance, are shown and discussed. The solutions are well received by the chief of surgery, who understands the potential use of this model, and possible advantages of the resulting schedule, comparing to the hospital schedule. Specifically, the chief of surgery considers the balance between the MSS and the surgeon's preferences a key goal to achieve. The result obtained for equal weights, in **Figure 6.1**, is considered the most appealing, since it represents a solution the hospital has not been able to reach yet. It is also agreed that, the hospital schedule presents better solutions for same cases, mainly when scheduling surgeries from the same surgeon, in the same day and sequentially, if possible, which does not always happen in the **Figure 6.1** schedule. For the surgeries with missing information, especially the ones without the surgical proposal available, the stakeholder also considers the hospital schedule a better solution. However, it is understandable that if the model had the whole information, it could eventually reach a suitable solution for those surgeries. Furthermore, usually, these two situations are related with the same surgeries. The surgeries without surgical proposal available, belong to the same surgeon, who probably asked sequential timeslots for all the surgeries. Thus, with the whole information available, the model could have attended to both these situations, in which the hospital schedule is considered better.

The model's potential use is acknowledged, however there are several setbacks needed to be solved, to allow the use of these models in their full potential. The model's solutions, and comparison with the real situation, show that by solving some management issues, the OR scheduling can be optimized using the developed model. The main concern indicated by the chief of surgery, is the incomplete information in the surgical proposals. This is also considered a limitation when applying the mathematical model to real data, and, is also makes OR scheduling much more challenging. An easy solution, proposed by the stakeholder, is an electronic surgical proposal, with mandatory fields and restrictions to the requests. The existence of this new proposal, definitely potentiates the model's performance and could increase the solution's quality.

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, independently of the number of weekly or monthly surgeries that surgeon will schedule. The intention is to attract more patients to the hospital, which is thought to be possibly achieved by having the maximum number of surgeons working there. This causes the previously mentioned 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 favorable in multiple ways. First of all, with less surgeons, the probability of overlapped surgical requests decreases, leading to an easier maximization of the surgeon's preferences. With an entire internal team, the MSS acceptance, and will to follow it, becomes more likely. It would even allow the surgeons to participate in building the MSS, optimizing the balance between MSS compliance and surgeon's preferences. The team work needed to have an efficient OR is also enhanced, if all team members work together daily. The OR scheduling can also be improved through strategies such as scheduling equal procedures sequentially, to ease the material flow and surgeon's work, since this type of strategies are easier to implement with an homogeneous, all internal, surgical team.

External surgeons usually do not have the hospital's best interest in mind, as much as an internal surgeon does. For instances, the external surgeon requests all kinds of material, without considering the costs for the hospital, if it provides financial return or if it will ever be used again for another procedure. Overall, an extreme number of external surgeons, scheduling their surgeries in the hospital, can be harmful to the OR management, which easily compromises the whole hospital management.

Another key-aspect mentioned by the chief of surgery, is the lack of reasonable duration estimates, by the surgeons in general. When predicting the time for the procedure, surgeons have the tendency to not only provide overachieving estimates, but also to exclusively consider the time their work takes. The surgery duration estimate has to consider the time the room is occupied, since that is the time needed to build the OR schedule. The surgeons may not include the turnover time in the estimate, which is easily added, but they can not only account for the time they are actually performing the procedure. At least the anesthesia time needs to be included, as the surgeon and the entire team have to be present for that. The time for certain protocols, mandatory before starting any surgery, also have to be considered. More realistic time estimates increase the probability of following the daily schedule, without avoidable delays, improving the OR efficiency.

The chief of surgery highlights the concern with the unsuitable use of the hospital infrastructures. Aiming again at attracting the maximum number of patients, the administration includes Ophthalmology as a surgical specialty. However, surgeries associated with this specialty are ambulatory surgeries, opposite to inpatient cases. The surgical floors in the case study, are only built for inpatients, and an ambulatory surgery unit does not exist. Therefore, ambulatory surgeries are being performed in a regular OR.

An ambulatory unit has a completely different structure. Patients do not need rooms with beds assigned, usually enter by their own feet in the OR, not needing the transporter employee, get undressed in a specific room and, after the procedure, recover within moments in a lounge, where they can be accompanied by family or friends. Procedures are consequently much faster, having a flow of patients entering and exiting the ambulatory OR much higher than in a regular OR. This type of patient pathway works completely different than the one seen for the case study OR. These surgeries are supposed to be separated from inpatients, and having them being performed in a regular OR compromises its workflow. In the hospital, the ambulatory patients take a longer time entering and exiting the OR, than the time usually associated with this type of patient. Consequently, a lower number of patients is treated, than it could be, if these were separated. When surgeons attempt to schedule and perform these ambulatory procedures, assuming the OR is suitable for them, schedules are not followed and the entire OR flow is damaged.

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 potentiating the hospital's growth, the overall efficiency decreases, the optimization becomes more difficult, decreasing profit and not providing better care.

Mixing ambulatory and inpatient procedures in the same schedule should be avoided. If surgeries must be handled differently, so does their schedule. It may not be very evident in the tests done in **Section 6.1**, because the instance is below the hospital's average production, but for a bigger instance, scheduling two types of surgeries simultaneously can have negative consequences. 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. This is an example of how "less, is more", and how the hospital's policy of always wanting a big number of surgeons and surgeries, can be harmful for themselves. Situations in which ambulatory surgeries prevent the OR from reaching a higher profit can disappear, if these surgeries are scheduled and performed separately.

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 6.1**, to integrate the parts in which the hospital schedule is considered superior, an ideal schedule can be achieved. The main changes would be, to remove surgeries scheduled over the weekend and join the surgeries, without the request available, that correspond to the same surgeon. 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. With the proper adjustments, this model has the potential to facilitate the job of the person responsible for the OR scheduling, as the final weekly schedule would only have to be validated by this worker.

6.3 Chapter Conclusions

This chapter presents the model's results using a real instance, and the comparison between the resulting schedule and the one used by the hospital, for the same week. It can be considered that the model's results can add value to the schedules being built currently by the hospital, as there is a clear difficulty when balancing the MSS compliance and following the surgeon's request.

Then, the main stakeholder, the chief of surgery, validates the model, allowing managerial insights. It can be inferred that the results highlight major issues occurring in the OR management, and support the chief of surgery's view in what concerns the changes necessary in the department. The work developed is received by the stakeholder with interest, and the potential of this tool is acknowledged. However, some changes may be necessary before implementing a scheduling tool in the department, to allow a use in its full potential.

Chapter 7

Conclusions and Future Work

In this chapter, the conclusions of the work performed are inferred. In addition, the limitations of the model are mentioned, and future work is suggested.

7.1 Conclusions

In hospitals, surgical services are a main source of income, but have major costs associated. The case study hospital is no exception, and optimizing the OR operations can provide a huge financial impact. With that in mind, a linear programming model is developed to optimize the OR surgery scheduling problem, a crucial aspect in OR management. The model is intended to be applicable in the hospital in study, so its structure is defined according to the hospital's needs and goals.

The OR holds several potential aspects to optimize, as the stakeholders easily identify the main sources of issues in the department. The uncontrollable number of surgical teams working and consequent team heterogeneity, is a cause for a decreased efficiency. It has been concluded that an homogeneous team allows the easier implementation and execution of tools like the MSS, and it improves the team work, enhancing the quality of the care provided. The incomplete surgical proposals submitted by the surgeons also cause issues, as they rarely fill the proposal properly, and often, essential information is omitted. The surgical proposal, filled properly, with all the key information needed to build a schedule, is definitely the first step to the OR scheduling optimization. Without a surgery duration or the requested team for the surgery, the schedule becomes much more difficult to build.

Elective surgery scheduling consists in a major study area within OR management, being constantly investigated, for more than 20 years now. Concerning the case study hospital, scheduling is identified as having a significant lack of efficiency inherent. It is essential to be aware of what has been done in this study area and know what is essential to consider and what can not be done, when developing this type of work. Therefore, a review of the existent literature is conducted and discussed.

The main objective identified, together with the stakeholders, is the balance between respecting the MSS implemented in the service and the surgeon's preferences. This goal is translated in the model as an objective with two parts, one corresponding to the MSS and the other to the surgeon's preferences, each one with a weight assigned, allowing to control this balance. The surgeon's preferences are translated into the day, hour and surgical team requested by the surgeon, for a surgery. The human resources, room and downstream unit capacities and types of rooms, according to the existent material that can not be transported, are included as constraints in the model. These constraints are also identified by the stakeholders as key aspects in the OR management.

A deterministic ILP model is developed and implemented. The model's performance is satisfactory, presenting, for all numerical tests, acceptable running times (all below one hour) and, with toy instances, optimization gap values equal or below 0.01%, and with a real instance an optimal gap value is always reached. The model is technically validated with two toy instances, including a weight variation analysis, concerning the objective that balances the MSS compliance and the surgeons preferences. The results for both toy instances allow to validate the model, and the weight variation confirms the influence of these weight values in the results. These weights enable a solution only considering the MSS, or a resulting schedule only taking into account the surgeon's requests. The balance initially aimed can also be achieved.

Using a real instance, the schedule achieves the objectives set, in a way the hospital has not been able to do. Although the available data corresponds to a week with a number of surgeries below average, the resulting schedule shows how useful this model can be to the hospital. When compared with the hospital schedule, for the same week, the schedule obtained through the model, considers the surgeon's request much more, without neglecting the MSS. However, the instance information is not complete, which limits the solution quality that can be reached.

When showing the work developed and the results to the main stakeholder, the chief of surgery, the potential of this work is recognized. The results highlight the main issues that are urgent to solve, before implementing a scheduling tool in the hospital. A main concern of the chief of surgery, is the absence of an electronic surgical proposal, that would definitely improve the model's performance and solution quality. By having an electronic tool, the usually omitted information, essential for the schedule, can be mandatory to fill in order to send the proposal. With the entire information needed for the model, the resulting schedule could potentially be better. At the same time, this new proposal would solve a major issue in the OR, which is the lack of information in the proposals submitted by the surgeons.

Concluding, the model has the potential to add value if inserted in the case study OR management, since, with the proper information available, it provides an optimized weekly schedule. In addition, it can also be modeled to provide a preferable balance between following the hospital's tactical strategies implemented, and maintain the surgeon's satisfied, by attending to their requests.

7.2 Limitations and Future Work

The main setback associated with this work is the limited access to real data. The profit margin values are not available to introduce in the numerical experiments. In addition, the available information is incomplete, which compromises the results. The absence of certain surgical proposals leads to an undesired schedule, at least for those surgeries. A clear evidence of this situation is the group of surgeries mentioned in **Chapter 6**, all from the same surgeon, that are scheduled across the week, instead of all sequentially in the same day, which is probably the surgeon's preference. In a situation where all objectives can be easily maximized, since both hospital and professionals interests are compatible, without that information, the model is not capable of providing the desired result. It becomes hard to maximize the surgeon's preferences when these are not all known.

The fact that all surgeon's do not entirely fill the surgical proposal, a problem mentioned in **Chapter 2**, also influences the numerical tests. The surgeon's preferences can only be taken into consideration in terms of day and hour, and even these are not all available. In what concerns the surgical team preferences, these are completely omitted in the proposals. When working as a team, which occurs daily in an OR, an essential aspect to maximize production and efficiency, is the good relationship between team members. This aspect can be optimized by the developed model, with the proper information provided.

Some limitations can guide the future work. In this work some limitations can be highlighted that indicate interesting paths to pursue in the future.

A significant concern is the postoperative unit scheduling, since there are cases of patients postponing their surgeries because there is no bed available for the postoperative phase. The bed capacity is considered in the model, however, this capacity changes each day, caused by daily entries and exits in this unit. To schedule the downstream unit, a different model should be done, to consider a different planning horizon. An independent schedule could be built, considering the LOS estimated by the surgeon. It also has to take into consideration, that the entry day for the patient might be the surgery day, or some day before the surgery, which is also defined by the surgeon. With a model that provides this schedule, the OR schedule can be built according to this one.

Uncertainty is inherent in certain aspects like the surgery duration, and a stochastic approach is usually utilized to deal with this uncertain parameter. As mentioned before, the model developed is deterministic, and it is mentioned by the hospital staff, that in most cases, the estimated duration is respected and this does not represent an issue in this surgical service. However, the uncertainty is inevitably associated with a parameter like the surgery duration, and it would approximate the model to the reality. Even more relevant than surgery duration, is to introduce uncertainty in the emergency cases appearance. Since it is previously explained that in case of an emergency the daily schedule might suffer changes, it would be interesting to take into consideration these emergency cases, as an uncertain feature. Not considering these emergency cases might also consist in a limitation for the model built.

Some suggestions for future work are mentioned by the chief of surgery. Namely, this stakeholder indicates the importance of scheduling equal surgeries (same procedure) sequentially. This is considered important, since it eases the material flow, and the team's work. This is translated into an extra constraint, that ensures, knowing the type of procedure of each surgery, that equal surgeries, have consecutive time blocks allocated. To add this constraint to the model, extra information has to be provided, namely, the type of procedure for each surgery. As the type of procedure is supposed to be in the surgical proposal, although it is not in most of the times, the information needed is available, if the proposals are filled properly.

The model already presents satisfactory results. By following some of these suggestions in the future, the model's potential to optimize surgery scheduling in the case study hospital 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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Appendix A

Instances Description

In this appendix are the tables missing from each instance description. Due to its length, these tables are removed from the respective chapters, and introduced here. **Table A.1** presents parameter θ_{se} on the left side, and each surgery's responsible surgeon, on the right side, for the first toy instance. **Table A.2** has the same information, for the 28 surgeries added to build the second toy instance.

Table A.3 includes, from left to right, for each surgery, the profit margin (p_s), estimated duration (d_s), requested day and hour (μ_{sdt}), requested anesthesiologist (μ_{asdt}) and nurses (μ_{nsdt}), for the first toy instance. The same information is described, for the additional 28 surgeries of the second toy instance, in **Table A.4**.

For the real instance, the parameter θ_{se} is described in **Table A.5**. **Table A.6**, from left to right, are the estimated duration (d_s), responsible surgeon and requested day and hour (μ_{sdt}), for each surgery of the real instance.

Table A.1: Parameter θ_{se} (left) and responsible surgeon for each surgery (right) for the First Toy Instance.

Surgical Specialty	**Surgeries**
1	5; 8; 15
2	6; 12; 16; 19
3	1; 2; 7; 11; 13; 20; 25
4	3; 14; 21
5	4; 9; 10
6	23; 28
7	24; 29
8	17; 27
9	18; 22; 26; 30

Surgeon	**Surgeries**
1	1; 7
2	5; 8; 15
3	4; 9; 10
4	2; 11; 13; 20; 25
5	6; 12; 16; 19
6	3; 14; 21
7	18; 22; 26; 30
8	17; 27
9	23; 28
10	24; 29

Table A.2: Parameter θ_{se} (left) and responsible surgeon for each surgery (right) for the last 28 surgeries of the Second Toy Instance.

Surgical Specialty	Surgeries
1	32; 41; 47; 48; 54; 56
2	34; 44
3	40; 43; 45
4	33; 49; 58
5	39
6	51
7	50
8	31; 38; 42; 46; 52; 55; 57
9	53

Surgeon	Surgeries
1	43
2	-
3	39
4	40; 45
5	34; 44
6	33; 49; 58
7	53
8	35; 42; 52
9	36; 51
10	37; 50
11	32; 41; 47; 48; 54; 56
12	31; 38; 46; 55; 57

Table A.3: Information for several parameters of the First Toy Instance. From left to right: p_s, d_s, mu_{sdt}, mu_{asdt}, mu_{nsdt}

			Surgeon Request		
Surgery	**Profit (euros)**	**Duration (hours)**	**Day and Hour**	**Anesthesiologist**	**Nurses**
1	2500	1	Monday, 11a.m.	2	2 + 4
2	860,5	2	Wednesday, 9a.m.	4	4 + 5
3	1260,8	4	Thursday, 8a.m.	1	1 + 3
4	1000	2	Monday, 8a.m.	2	2 + 6
5	3000,24	3	Friday, 11a.m.	3	9 + 8
6	1780,1	2	Tuesday, 9a.m.	4	8 + 9
7	965,2	1	Wednesday, 10a.m.	1	5 + 4
8	798,16	4	Thursday, 4p.m.	2	10 + 1
9	599,35	4	Friday, 8a.m.	3	10 + 8
10	860,5	3	Monday, 1p.m	1	10 + 6
11	2530	2	Saturday, 7p.m.	2	3 + 5
12	862,5	2	Tuesday, 2p.m.	2	6 + 7
13	1270,8	1	Wednesday, 6p.m.	4	7 + 9
14	1070	2	Tuesday, 11a.m.	4	2 + 10
15	3080,24	3	Saturday, 12a.m.	1	3 + 10
16	1750,1	2	Friday, 8a.m.	3	6 + 7
17	945,2	4	Saturday, 4p.m.	3	7 + 3
18	1098,16	3	Monday, 6p.m.	4	8 + 5
19	799,35	2	Tuesday, 8p.m.	1	3 + 1
20	1860,5	3	Wednesday, 5p.m.	2	5 + 4
21	1860,5	4	Thursday, 6p.m.	3	4 + 6
22	1530	4	Tuesday, 4p.m.	4	6 + 9
23	872,5	3	Wednesday, 10a.m.	1	8 + 7
24	1470,8	2	Thursday, 6p.m.	3	9 + 10
25	1079	2	Friday, 11a.m.	2	2 + 3
26	2080,24	1	Friday, 1p.m.	1	3 + 6
27	1760,1	2	Thursday, 4p.m.	2	4 + 6
28	985,2	3	Wednesday, 6p.m.	3	8 + 2
29	1598,16	2	Saturday, 8a.m.	4	6 + 5
30	1799,35	2	Tuesday, 12a.m.	1	7 + 3

Table A.4: Information for several parameters of the last 28 surgeries of the Second Toy Instance. From left to right: p_s, d_s, mu_{sdt}, mu_{asdt}, mu_{nsdt}

			Surgeon Request		
Surgery	**Profit (euros)**	**Duration (hours)**	**Day and Hour**	**Anesthesiologist**	**Nurses**
31	1950,8	4	Friday, 9:30a.m.	2	5 + 6
32	1320,6	4	Saturday, 10:30a.m.	1	8 + 10
33	1020,5	3	Tuesday, 8a.m.	3	3 + 15
34	598,3	2	Tuesday, 11:30a.m.	3	7 + 1
35	798,16	2	Thursday, 11a.m.	1	4 + 12
36	599,35	1	Wednesday, 8a.m.	4	11 + 14
37	860,5	2	Thursday, 4p.m.	4	11 + 2
38	2530	3	Friday, 4p.m.	3	5 + 3
39	862,5	2	Monday, 10a.m.	4	10 + 9
40	1270,8	3.5	Monday, 2:30p.m	2	7 + 13
41	1070	3	Saturday, 4p.m.	3	2 + 4
42	3080,2	2	Thursday, 2p.m.	4	11 + 9
43	1750,1	3	Wednesday, 12a.m.	2	2 + 6
44	945,2	4	Tuesday, 4p.m.	4	5 + 4
45	1098,2	4	Monday, 6p.m.	1	15 + 13
46	799,35	3.5	Saturday, 11a.m.	3	1 + 9
47	1860,5	3	Friday, 9a.m.	4	4 + 8
48	2500	2	Friday, 12a.m.	1	7 + 14
49	860,5	3	Tuesday, 2:30p.m.	3	6 + 12
50	1260,8	3.5	Thursday, 10a.m.	4	3 + 8
51	1000	3.5	Wednesday, 2:30p.m.	4	2 + 9
52	3000,2	2.5	Thursday, 6:30p.m.	2	4 + 10
53	1780,1	2	Monday, 3:30p.m.	1	3 + 12
54	965,2	2	Monday, 10a.m.	2	15 + 13
55	798,16	1	Wednesday, 9a.m.	2	5 + 9
56	599,35	2	Monday, 8a.m.	3	10 + 2
57	860,5	2	Wednesday, 10:30a.m.	4	11 + 1
58	2530	2.5	Thursday, 3p.m.	3	14 + 3

Table A.5: Parameter θ_{se} related to the Hospital Instance.

Surgical Specialty	**Surgeries**
1	5; 6; 7; 8; 13
2	12
3	30; 31; 32; 33; 34; 35; 36; 39
4	1; 2; 14; 15; 16
5	9; 10; 11; 18; 19; 23; 24; 25; 26; 27; 40; 41; 42; 43; 44; 45; 46
6	37; 38
7	13
8	3; 4; 28; 29
9	17; 20; 21
10	22

Table A.6: Information for several parameters concerning the Hospital Instance. From left to right: d_s, responsible surgeon, μ_{sdt}.

Surgery	**Duration (hours)**	**Surgeon**	**Surgeon Request**
1	1.5	1	Monday, 3:30p.m.
2	1.5	1	Wednesday, 4p.m.
3	1	11	Not Available
4	1.5	11	Tuesday, 2:30p.m.
5	1.5	13	Tuesday, 10a.m.
6	1.5	13	Wednesday, 6p.m.
7	3.5	13	Friday, 8a.m.
8	2	13	Thursday, 8a.m.
9	2.5	2	Tuesday, 9a.m.
10	2.5	2	Monday, 9a.m
11	2.5	2	Monday, 12a.m.
12	1	12	Tuesday, 8a.m.
13	1.5	21	Friday, 8a.m.
14	1.5	15	Wednesday, 9a.m.
15	1	15	Tuesday, 10a.m.
16	1.5	15	Wednesday, 10a.m.
17	2.5	18	Monday, 8a.m.
18	2.5	3	Monday, 8a.m.
19	1.5	20	Not Available
20	2	4	Monday, 8a.m.
21	2	4	Monday, 6p.m.
22	1.5	22	Friday, 10a.m.
23	1.5	14	Wednesday, 11a.m.
24	1.5	14	Wednesday, 1p.m.
25	1.5	14	Wednesday, 3p.m.
26	1.5	5	Monday, 8a.m.
27	1	16	Tuesday, 8a.m.
28	1.5	6	Monday, 4p.m.
29	3	6	Monday, 5p.m.
30	0.5	17	Not Available
31	0.5	17	Not Available
32	0.5	17	Not Available
33	0.5	17	Not Available
34	0.5	17	Not Available
35	0.5	17	Not Available
36	0.5	17	Not Available
37	1	19	Thursday, 2p.m.
38	3.5	19	Thursday, 3p.m.
39	0.5	7	Not Available
40	2	8	Friday, 6p.m
41	3	9	Tuesday, 10a.m.
42	2	9	Tuesday, 8a.m.
43	3	9	Thursday, 8a.m.
44	2.5	9	Thursday, 11a.m.
45	2	10	Monday, 8a.m.
46	1.5	10	Monday, 10a.m.