How to Improve Surgical Production and Stakeholders' Satisfaction?

The Portuguese Case of CHLN and HESE

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Dissertation to obtain the Master of Science Degree in

Industrial Engineering and Management

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December 2020

Declaração

Declaro que o presente documento é um trabalho original da minha autoria e que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

Declaration

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

À minha mãe, ao meu pai, à Ana e ao Hélder.

Acknowledgments

Following this long journey, I would like to express my sincere gratitude to all those who helped me reach the end of another major milestone.

To Professor Inês Marques and Dr Daniel Santos, who supported me in setting a path in this work, sharing knowledge and ideas, and who accompanied me in all my doubts and difficulties.

A warm thank you to all my family and their unconditional love, to my parents, Isabel and Miguel, to Ana and Hélder and to my grandparents who gave me foundations and tools to walk the upcoming paths. To my sisters, Marta, Matilde, Margarida, Sofia and Sara, whom I love, and who put up with me in any circumstance and at any time.

To all my friends and colleagues, who I had the pleasure of sharing this journey with, thank you for all the moments of happiness which I am sure will stay for life. And to the future moments that have been postponed and that will have to remain until after this pandemic.

At last, I wish to thank Francisca, who has always been by my side in this challenging journey, for always believing in me and in the success of this work – *A mais caminhadas em conjunto*.

Abstract

The Portuguese National Health Service case on surgery production is characterized by long waiting lists and the inability of meeting all demand in the guaranteed time, with 20% more demand than supply capacity. With the main objective of improving the supply of surgical care and increasing resource utilization efficiency, the operating room planning and scheduling problem is widely studied in the literature. However, for hospital administrations, choosing a scheduling model is not simple, since the models are not directly comparable, employing different objectives and parameters, which are tested in different instances.

Currently, no fair comparison of models exists in the literature; this dissertation’s objective is to develop a benchmark of models on the operational level of operating room planning and scheduling according to established key performance indicators. A literature review is performed and the reviewed papers are analysed and schematically classified under four tailored domains. According to defined criteria, the models of three papers are selected to partake in the benchmark. The instances used in the computational experiments are provided by two Portuguese public hospitals.

Results of the benchmark show that the findings vary according to the models, instances and indicators being tested. No dominance between models has been found although the surgeons’ model of Marques and Captivo (2017) fails to adequately perform in most indicators, mainly patient and surgeon focused indicators. The creation of a decision support model to assign value functions in each criterion and weighs between the criteria is necessary to achieve a hierarchy between models.

Keywords: Operating Room Scheduling; Optimization Models; Mixed Integer Programming; Stake-holders; Benchmarking; Performance Assessment.

Resumo

O caso do Serviço Nacional de Saúde na produção cirúrgica é caracterizado por longas listas de espera e incapacidade de satisfazer a procura no tempo garantido, com 20% mais procura do que capacidade de oferta. Com o objectivo principal de melhorar a oferta de cuidados cirúrgicos e a eficiência na utilização de recursos, o problema do planeamento e calendarização do bloco operatório é amplamente estudado na literatura. Contudo, para administrações hospitalares, a selecção de um único modelo de calendarização não é viável, dado que os modelos não são directamente comparáveis por recorrem a diferentes objectivos, parâmetros e instâncias.

Por não existir uma comparação de modelos na literatura, o objectivo da dissertação é desenvolver uma avaliação comparativa de modelos ao nível operacional da calendarização do bloco, de acordo com indicadores estabelecidos. É realizada uma revisão bibliográfica e os artigos revistos são analisados esquematicamente em quatro domínios. De acordo com critérios definidos, os modelos de três artigos são seleccionados para participar na avaliação. Os dados utilizados nas experiências computacionais foram cedidos por dois hospitais públicos portugueses.

A avaliação mostra que existe uma variação entre resultados de acordo com modelos, instâncias e indicadores a serem testados. Não foi encontrada dominância entre modelos, embora a surgeon's version de Marques e Captivo (2017) apresente um fraco desempenho na maioria dos indicadores, principalmente nos centrados em pacientes e cirurgiões. A criação de um modelo de apoio à decisão para atribuir funções de valor e pesos entre critérios é necessária para alcançar uma hierarquia entre modelos.

Palavras-chave: Calendarização do Bloco Operatório; Modelos de Optimização; Programação Inteira Mista; *Stakeholders*; Avaliação Comparativa; Avaliação de Desempenho.

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CAHS - Central Administration for the Health System

CHLN - Centro Hospitalar Lisboa Norte

COT - Central Operating Theatre

FCFS - First-Come-First-Served

HESE - Hospital Espírito Santo de Évora

HPV - Hospital Pulido Valente

HSM - Hospital Santa Maria

ICU - Intensive Care Unit

KPI - Key Performance Indicator

LIC - *Lista de Inscritos para Cirurgia*, Surgery Waiting List

LOS - Length of Stay

LVT - Lisboa e Vale do Tejo

MSS - Master Surgery Schedule

OECD - Organisation for Economic Co-operation and Development

OR - Operating Room

OT - Operating Theatre

OTR - Otorhinolaryngology

PACU - Post-Anaesthesia Care Unit

PHU - Preoperative Holding Unit

PPP - Public-Private Partnership

RHA - Regional Health Administration

SIGIC - *Sistema Integrado de Gestão de Inscritos para Cirurgia*, Integrated System for Surgery Waiting List Management

SIH - *Sistema de Informação Hospitalar*, Hospital's Informatics System

SNS - *Serviço Nacional de Saúde*, National Health Service

SSP - Surgery Scheduling Problem

TMRG - *Tempo Máximo de Resposta Garantido*, Maximum Guaranteed Response Time

1 Introduction

1.1 Problem Background and Motivation

Established in 1948, the Universal Declaration of Human Rights states in article 25 that "*everyone has the right to standard of living adequate for the health and well-being of himself and of his family*" (UN General Assembly 1948). According to what is acknowledged, the state has the duty to ensure and promote the right of health. However ensuring health to all citizens is becoming more demanding as the conditions of the population keep changing (Perrott and Holland 2005). Some of the most important factors are the rate of population growth alongside with a higher life expectancy, changing the age structure, and increasing the elder population proportion. Internal migrations from rural to urban areas have caused an unbalancing of existing health infrastructures and a need for continuous review of the health system.

The expenditure in the health sector in Portugal in 2018 represented a major component in the total state budget, with 18,3B € and 9,1% of the total Gross Domestic Product (INE 2020a). In this system, hospital care represents a large stake of all health care provided by the state, with 7,7B € of budget investment in 2018, approximately 43% of the total health expenditure. In hospitals, representing more than 40% expenditure and revenue, the operating theatres (OT) are one of the most important departments (Beliën et al. 2009). In 2018, there were 970 234 surgeries performed, of which 594 978 in Portuguese public hospitals, with 244 501 patients awaiting surgery in the same year (INE 2020c; Ministério da Saúde 2019). In Figure 1, the evolution of performed surgeries in public hospitals and the number of new registrations for surgeries is shown. On average, the ratio between the number of new registrations for surgery per day and the number of executed surgeries per day is 1,18, meaning that the demand for surgeries is higher than the supply.

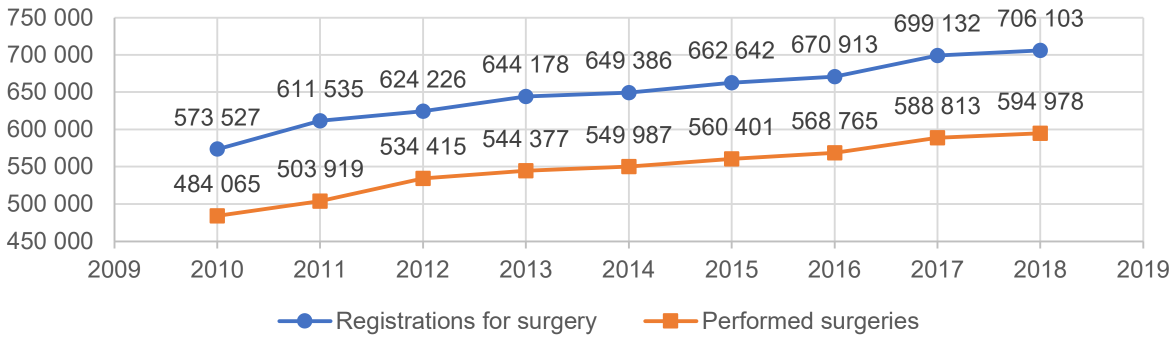

Figure 1 – Annual registrations for surgery and performed surgeries (from Ministério da Saúde, 2019)

The optimization of these services is therefore essential, not only to employ the given budget as efficiently as possible but also to answer the high surgery demand observed. Regarding the OT, several measures can be taken to better optimize the service. The most developed in the literature concerns operating room (OR) planning and scheduling. Creating an optimized schedule that suits all stakeholders is one of the major difficulties for OR managers. On the one hand, part of these difficulties arises due to numerous complex and conflicting constraints. On the other, several times, the objectives to achieve are not well established. These objectives can also be conflicting, with different stakeholders having preferences and asking for performance in distinct indicators. Clear prioritization of key performance indicators (KPIs) needs to occur so the planning and scheduling can be optimized.

In OR planning and scheduling literature, multiple papers are published, with different approaches regarding the decision levels, which constraints to take into consideration and which objectives to respond to (Zhu et al. 2019). These papers also work with distinct instances which makes them hard or impossible to compare directly. Apart from these publications, there are also many literature reviews such as Cardoen et al. (2010); Guerriero & Guido (2011); Van Riet & Demeulemeester (2015); Samudra et al. (2016) and most recently Zhu et al. (2019) that review and organize the existing papers within designed criteria. Despite new papers being published each year, the real application of these new and revised methodologies in daily hospital operations is very low (Cardoen et al. 2010; May et al. 2011; Zhu et al. 2019). Furthermore, it is very difficult for OR managers to choose one literature-based methodology over others since, as said, they are not directly comparable, and no benchmarks are available.

1.2 Dissertation Goals

The impossibility to compare different models and approaches in the current literature leads to the dissertation's research objective – develop a benchmark of OR scheduling models published in literature. The selected models are tested using normalized instances from two Portuguese hospitals. Also, an evaluation matrix adjusted to the Portuguese National Health Service, Serviço Nacional de Saúde (SNS) and other stakeholders' objectives is constructed to compare those models. This dissertation is a result of a partnership between Instituto Superior Técnico and two hospitals belonging to the SNS, Centro Hospitalar Lisboa Norte (CHLN) and Hospital Espírito Santo de Évora (HESE). Real data from these hospitals and instances publicly available in the literature will be used for the computational experiments.

The aim of this work is thus twofold – characterize the problem in sutdy, presenting the current situation both in hospital perioperative processes and in the literature, and perform a benchmark on selected models to compare the outcome solution in line with the KPIs valued by the SNS and other hospital stakeholders. The main contributions of this work to literature are:

i. Extension of the work of Zhu et al. (2019), obtaining an updated and structured literature review on the operational level of the OR planning and scheduling problem;
ii. Development of a benchmark of models in literature using standardized instances;
iii. The creation of an evaluation matrix of KPIs having in account multiple stakeholder's points of view.

1.3 Methodology Proposal

Under this objectives, the methodology of the dissertation is now presented. The outline of the methodology is shown in Figure 2. This is structured in eight steps: 1. Case Study and Problem

Definition, 2. Literature Review, 3. Selection and Adaptation of Models, 4. Data Collection, 5. Model Validation, 6. Creation of an Evaluation Matrix, 7. Result Analysis, and finally, 8. Recommendations for the Hospitals.

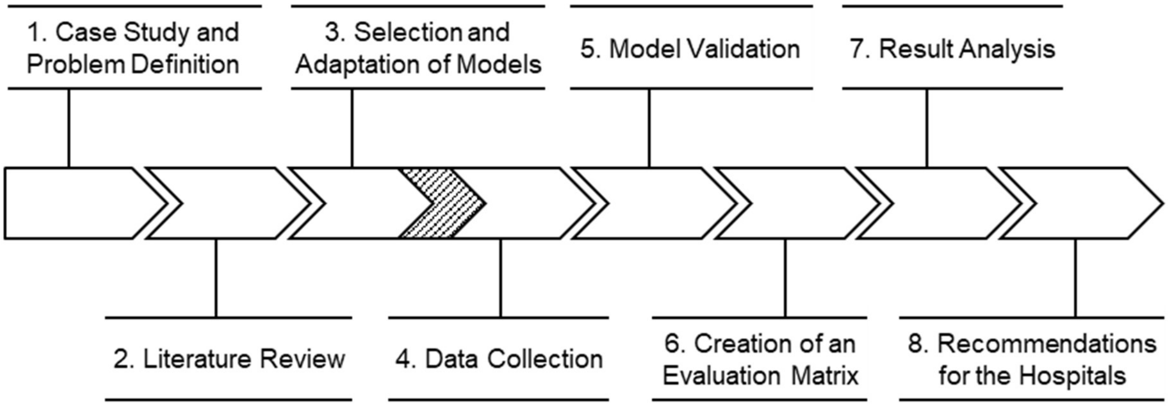

Figure 2 – Schematic representation of the methodology proposal

1. Case Study and Problem Definition – The first step intends to provide an overview of the SNS, and particularly, the cases of CHLN and HESE, contextualizing the reader with the surgery scheduling process at the hospitals and its challenges. Furthermore, attending to the specific case studies, the problem studied is presented in more detail.
2. Literature Review – The objective of the literature review is to understand and give a comprehensive insight on the state-of-the-art on the operational level of OR planning and scheduling problem, following a structured framework.
3. Selection and Adaptation of Models – Based on the literature, a group of models is selected to participate in a benchmark. The selection of these models is made according to the characteristics that best suit the case studies presented.
4. Data Collection – This step consists of gathering and treatment of data from CHLN and HESE used in the models. As represented in Figure 2, the previous, third step and the fourth interact between them in an iterative process. As the data collected differs from the instances used originally in the models, possible adaptations to certain parameters may have to occur. The objective is to perform as less adaptations as possible to stay aligned with the original models and provide a fair benchmark.
5. Model Validation – In this step, the four selected models are validated through the instances collected in the previous step to confirm that the results of the selected models are acceptable and consistent with the real data used.
6. Creation of an Evaluation Matrix – The objective is to design an evaluation matrix based on the performance indicators that are most valued by the stakeholders. In contrast to most situations in Operations Research where solutions are evaluated with their specific objective functions, the evaluation matrix allows for solutions to be evaluated through standard criteria.
7. Result Analysis – The output results from the selected models are evaluated according to the evaluation matrix. This step comprises the benchmark itself, where model solutions are compared, so the decision-makers can clearly see how each solution performs on the selected KPIs.

8. Recommendations for the Hospitals – The methodology finishes with recommendations and insights based on the analysis of the obtained results. These recommendations tackle the operational level on scheduling patients, but with the expectation of improving on efficiency, a bottom-up analysis can be made to understand if there is a need to restructure the strategic and tactical levels.

As mentioned, steps 1-8 are the methodology to be followed in the present dissertation, so to assess the performance of multiple solutions and compare them to what is being performed in real SNS hospitals, according to multiple stakeholder's KPIs and preferences.

1.4 Dissertation Structure

To address the needed areas, the remaining of this document is structured in six chapters:

Chapter 2, Case Studies, presents an overview of the Portuguese health sector, SNS, and in particular of the hospitals CHLN and HESE. The insights about surgery procedure in SNS and the surgery scheduling in both public hospitals under study are portrayed. To accomplish that and to bring the reader abreast with the used terminology, a patient classification scheme is used. A description of the involved stakeholders in surgery and surgery planning, and also the KPIs employed to measure OR performance is taken. The chapter concludes with the definition of the problem under study.

Chapter 3, a Literature Review is performed according to four domains, namely decision level, patient characteristics, scheduling strategy, and problem features. The literature review ends with a conclusion on the state-of-the-art and a highlight on the contributions of this work to the current literature.

Chapter 4, Selection and Adaptation of the Models, begins by presenting the screening criteria in order to assess the models that can be implemented. Evaluation criteria are also employed to choose the models that best suit the thesis' objectives of improving surgical production while also attending the stakeholders' needs. Three models are chosen, namely Kamran et al. (2018), Marques and Captivo (2017), and Moosavi and Ebrahimnejad (2020). An overview and formulation of each mathematical model is also presented. The chapter is concluded with a first theoretical comparison of the models.

Chapter 5, Data Collection and Parameters Specification, details the data gathered from both hospitals, required to apply the model to the case studies. Furthermore, parameters for all models being tested are described, along with required assumptions and limitations.

Chapter 6, Results and Discussion, presents the evaluation matrix of KPIs and the results of the computational experiments performed with the selected models. The models' findings are subject to analysis and comparison, not only in the light of chosen KPIs but also in regard to the actual surgical plan of CHLN that was made available by the hospital.

Chapter 7, Conclusions and Future Work, closes the dissertation with the work's conclusions, main achievements and findings, presenting opportunities as well for future research.

2 Case Studies

This chapter presents a characterization of the problem and gives the reader an overview of the OR planning and scheduling process in Portugal. In Section 2.1, the Portuguese national health service organization is introduced and then, the hospitals under study, CHLN and HESE, are depicted. Section 2.2 describes the physical properties of each hospital's OT. The description of the patient's flow in the context of surgery is presented, in Section 2.3, in order to understand the actual surgery scheduling process in both hospitals. In Section 2.4, alongside with the identification and characterization of the involved stakeholders, and according to each of them, measurable objectives are defined and explained so it is possible, in Section 2.5, to describe the problem under study in this work. The chapter ends with the main conclusions in Section 2.6.

2.1 Hospitals CHLN and HESE in SNS

Each healthcare system has its particular characteristics, although the transfer of the individual's financial risk to an external entity is an intrinsic element in each coverage, regardless of the system adopted. According to the model used by OECD for the Health System Characteristics project (Joumard et al. 2010), it is possible to classify three types of health insurance coverage based on the way the beneficiaries adhere. Namely automatic adhesion, mandatory adhesion, and voluntary adhesion systems. The first one, automatic adhesion, regards tax-funded health systems where the State takes on the role of Health insurer, the responsibility for financing, ownership of the health-related material assets and management of the network of all health care providers. Mandatory adhesion is linked to the payment of social contributions or risk-rated premiums for defined social groups. These are occupational health protection systems – known as health subsystems (Braun and Centeno 2018). Finally, the model of coverage through voluntary adhesion consists of the adhesion to individual insurance through the payment of a risk premium – private insurance. This system is mainly sought when there is a deficiency in the coverage or the quality of the other existing models.

The health system in Portugal consists of these 3 systems that co-exist and overlap (Simões et al. 2017). Although every Portuguese citizen is covered by SNS, according to ASF, (2018) 19% of the population is also covered by a health subsystem and 11.7 % have private insurance.

In Subsection 2.1.1 an overview of the Portuguese national health service is given, followed by a description of the hospitals under study, CHLN and HESE, in Subsection 2.1.2 and 2.1.3 respectively.

2.1.1 The SNS

The SNS was founded in 1979 with the primary objective of guaranteeing access and coverage to all population, a right defended by the 1976 Portuguese Constitution. In this context, hospitals and other health facilities belonging to social systems or religious entities, such as *Misericórdias*, were brought under the new SNS (Simões, 2010). The Lei de Bases da Saúde (law establishing the basis of health) recognizes the SNS as a service with its own statute, regionalised organisation, and decentralised and participatory management (cf. *base* 20 of Lei n.º 95/2019 de 4 de Setembro).

Since its establishment, the SNS has gradually progressed, both in the supply and organisation of services, resources and their management (Ministério da Saúde 2018). In 1993, SNS proceeded to the creation of 5 regions (*Norte, Centro, Lisboa e Vale do Tejo - LVT, Alentejo,* and *Algarve*), each with its own Regional Health Administration – *Administração Regional de Saúde* (RHA). RHAs were formed with the aim of allowing a better allocation of resources and reducing inequalities in health, with decentralised management. The Central Administration for the Health System – *Administração Central do Sistema de Saúde, I.P.* (CAHS), founded in 2007, is the central body responsible for coordinating and monitoring the SNS under the guidance of the Ministry of Health.

As can be seen in Figure 3, the RHAs are responsible for the management of public primary health care units and public hospitals. Regarding monetary flows, the SNS is mainly financed through taxes and direct, out of pocket payments. Out of pocket payments represented 27.6% of total health expenditure in 2015 (Simões et al. 2017). Primary health care units are fully financed by the respective RHA. Regarding hospitals, the funding is mixed, being part contracted with the RHA and the rest directly through the CAHS. According to Simões et al. (2017), both management and autonomy over funding continue to be quite centralised, despite the creation of the RHAs.

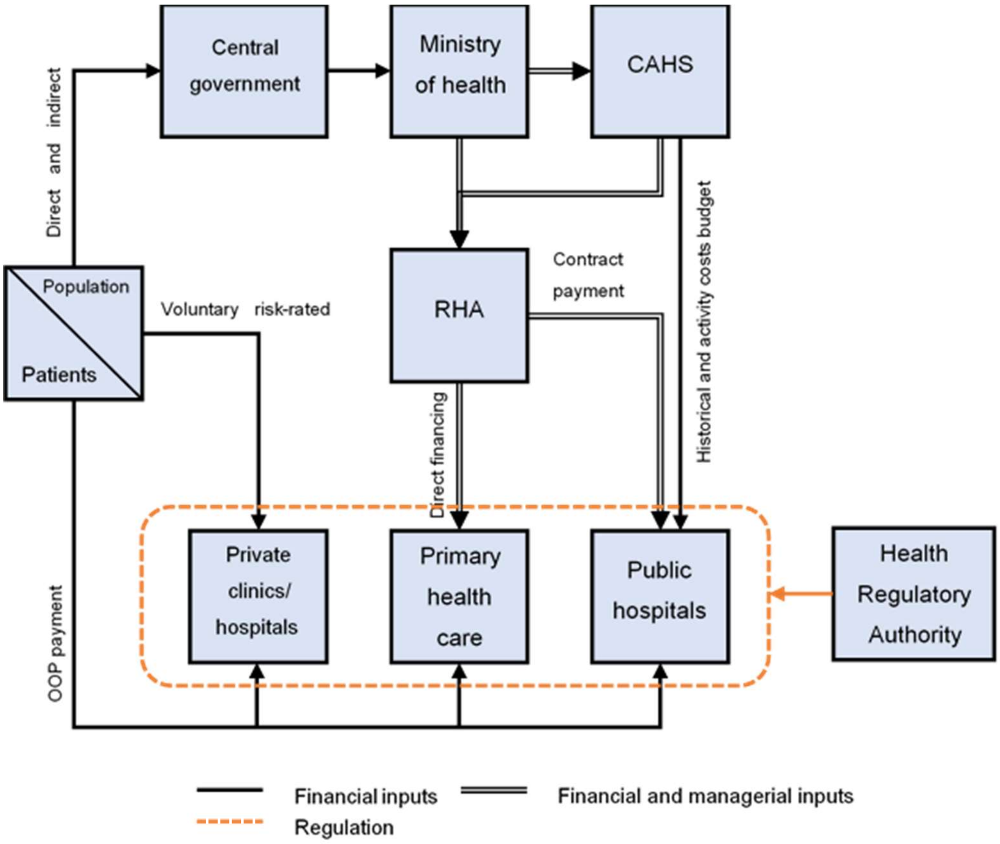

Figure 3 – Overview of the financial flows in the SNS (adapted from Simões et al., 2017)

Regarding the hospital sector, there are currently 230 hospitals in Portugal, of which 111 are public and public-private partnership (PPP), an integral part of the SNS, and 119 are private (INE 2020c). Those

111 public hospitals are divided into 50 hospital institutions, of which 39 are hospital centres and hospitals, 3 are PPP hospitals and the remaining 8, local health care units[i].

2.1.2 CHLN

The Centro Hospitalar Universitário de Lisboa Norte, E.P.E. (CHLN) is located in the Lisbon Metropolitan Area and is part of LVT RHA. It is composed by Santa Maria University Hospital, E.P.E. (HSM) and Hospital Pulido Valente, E.P.E. (HPV). The two hospitals, administered by the same president since April 2007, were aggregated on March 1, 2008 by *Decreto-Lei n.2 23/2008*, being classified as group III or central hospital.

The area of direct influence of CHLN corresponds to the *Unidade Setentrional de Lisboa* – Unit of Northern Lisbon (including parishes Alvalade, Avenidas Novas, Benfica, Campolide, Carnide, Lumiar, Santa Clara and São Domingos de Benfica), and it is aimed at a total population of more than 329,000 inhabitants (INE 2020b). Besides the population of the area of direct influence, the CHLN can also provide care to users from all over the national territory and in occasional situations to foreign citizens in transit, holidays or residents in Portugal and cases of repatriation due to health emergency.

Despite their centrality, HSM and HPV have distinct and complementary characteristics that have enabled better integration: HPV has high specialization in the areas of intervention, although less versatile; HSM, stands out for diversity in the various areas of medicine, sharing the space with the Faculty of Medicine of the University of Lisbon and the Institute of Molecular Medicine. The current model allows for more adequate management of the differentiated health care units in question, in order to obtain the maximization of the resources involved, a reduction in operating costs, as well as gains in productivity and efficiency[ii].

Since part of the instances used in this thesis benchmark are provided by the CHLN hospital, it is essential to observe the activity of programmed or elective surgeries in the hospital and its evolution in the past years, from 2014 until 2019 (Table 1). In Table 1 it is also possible to compare the number of surgeries with the performed value in the LVT region and the rest of Portugal. These values consider only elective surgeries. As can be seen, CHLN is responsible for approximately 15,58% of LVT elective surgical production in 2019, where there are 14 other hospital institutions that perform surgery. It is evident that CHLN is, in fact, a major hospital with great significance in terms of production in the area.

Table 1 – No. of programmed surgical interventions in CHLN, LVT RHA and Portugal (SICA 2020)

	2014	**2015**	**2016**	**2017**	**2018**	**2019**
CHLN	29 779	31 746	32 614	32 411	29 461	30 031
% of LVT RHA	16,98%	18,28%	18,02%	17,15%	15,64%	15,58%
LVT RHA	175 396	173 710	181 007	188 947	188 359	192 806
Portugal	546 273	552 468	565 743	575 834	572 476	604 294

[i] https://www.sns.gov.pt/institucional/entidades-de-saude/ Consulted on 8th May 2020
[ii] https://dre.pt/application/conteudo/248228 Consulted on 8th May 2020

Through the last CHLN's Activity Plan and Budget (CHLN 2019) it is possible to access that the average length of stay is 8,74 days. The average occupancy in the hospital centre for 2017 was 961 out of 1 110 beds which meant an occupancy rate of 86,58%, close to 85% considered the threshold of waste of resources.

The central operating theatre (COT) in HSM serves five surgical specialities, namely general surgery, orthopedy, vascular surgery, urology and gynaecology, plus emergencies. All other speciality surgeries are performed in peripheral and dedicated ORs. In Table 2, the number of elective and non-elective surgeries are presented separately. Both types of surgeries are detailed on Subsection 2.3.1 and depend on the type of admission. It is possible to see that the total number of elective surgeries has been stable from 2014 to 2019, but with a continuous significant decrease in conventional (or inpatient) surgery and an increase in ambulatory (or outpatient) surgery. This increase in ambulatory surgeries is explained by the pressure from CAHS and the SNS to opt for this type of surgery whenever possible, instead of performing a conventional one, through incentives defined in hospital contracts. Opting for ambulatory surgery decreases the time the patient is at the hospital, reducing risk of hospital infections and increasing the turnover of beds. The total number of non-elective surgeries has slightly increased as well. Most of these surgeries can occur in HSM's COT in five OTs with two operating rooms each, detailed in Subsection 2.2.1.

Table 2 – Detailed surgical production in CHLN (SICA 2020)

	2014	2015	2016	2017	2018	2019
Elective	29 779	31 746	32 614	32 411	29 461	30 031
Conventional	16 184	16 231	15 656	13 275	11 212	10 547
Ambulatory	13 585	15 515	16 958	19 136	18 249	19 484
Non-elective	5 181	5 323	5 637	6 005	6 161	5 977
Total	34 960	37 069	38 251	38 416	35 622	36 008

While HSM serves elective and non-elective surgeries, HPV only has the elective ambulatory surgery service. It is composed of eight specialities, namely general surgery, orthopedy, vascular surgery, cardiothoracic surgery, stomatology, otorhinolaryngology (OTR), neurosurgery and plastic surgery. In this work, only the COT of HSM will be under study as the information and data on peripheral ORs and ORs from HPV is not centralized and thus more difficult to obtain.

2.1.3 HESE

The Hospital Espírito Santo de Évora, E.P.E. (HESE) is located in Évora, Alto Alentejo, and is part of the Alentejo RHA. Initially, HESE belonged to the *Santa Casa da Misericórdia de Évora* (since 1567) and passed to the jurisdiction of the State on April 2, 1975. In 2008, through *Portaria n.º 117/2008*, the hospital was classified from group II or regional hospital to group III, central hospital.

The hospital's area of direct influence covers the entire district of Évora, covering 14 municipalities, with a total of 152 865 inhabitants. Besides the area of direct influence, HESE also has an indirect area of influence that covers the entire region of Alentejo, corresponding to 33 municipalities with a population of 319 000 inhabitants in Alto Alentejo, Baixo Alentejo e Alentejo Litoral (INE 2020b). As a central hospital, there are several medical specialities from Alentejo RHA that are only present in HESE. As an example, HESE is the only hospital with an intensive care unit (ICU) for cardiology and thus most patients requiring cardiology interventions in Alentejo are sent to HESE.

According to the information present on the hospital's website[i], all units in the hospital have been improving in terms of production, turnover, and utilization over recent years. In 2018 there was a significant improvement in most HESE production lines. The number of elective surgical interventions has been in constant growth since 2017 as can be seen in Table 3. In 2019 there were almost 24% more surgeries than 2014, totalling 16 724 elective surgical interventions. Despite the constant growth since 2017, the hospital points to the difficulty felt in the OT in relation to human resources but does not specify the causes or actual repercussions. The number of surgeries performed in HESE represents more than 55% of the value in Alentejo RHA, where there are 4 hospitals performing surgeries.

Table 3 – No. of programmed surgical interventions in HESE, Alentejo RHA and Portugal (SICA 2020)

	2014	2015	2016	2017	2018	2019
HESE	13 491	12 553	12 737	11 610	14 590	16 724
% of Alentejo RHA	52,71%	49,19%	46,59%	45,45%	52,78%	56,51%
Alentejo RHA	25 593	25 521	27 338	25 544	27 645	29 590
Portugal	546 273	552 468	565 743	575 834	572 476	604 294

To face the constant rising demand, the hospital has also extended its capabilities, adding two buildings to the original one, the *Espírito Santo* building. The first extension occurred in 1975 and comprises, among others, the OT studied in this thesis. Although the newest building construction started shortly after to become a separated oncological hospital, *Patrocínio* only started operating in 2000, to face the demand in external consultations, as part of HESE and now consists of the internment area, external consultations, and oncology of HESE.

Table 4 – Detailed surgical production in HESE (SICA 2020)

	2014	2015	2016	2017	2018	2019
Elective	13 491	12 553	12 737	11 610	14 590	16 724
Conventional	4 922	5 005	4 604	4 194	4 783	5 561
Ambulatory	8 569	7 548	8 133	7 416	9 807	11 163
Non-elective	1 599	1 487	1 378	1 449	1 700	1 779
Total	15 090	14 040	14 115	13 059	16 290	18 503

The COT in HESE serves 8 surgery specialities, namely general surgery, orthopaedics, urology, ophthalmology, plastic surgery, paediatric surgery, OTR and stomatology, plus emergencies. Gynaecology is performed in the maternal OT which is located at a separate part of the hospital. Table 4 presents the numbers for elective and non-elective surgeries separately. The value of elective production has risen in the last three years, as seen before, but similarly to CHLN, the main increase

[i] http://www.hevora.min-saude.pt/2019/12/27/o-hospital/ consulted on 2nd April 2020

stands on the ambulatory surgery rather than the conventional. The number of non-elective surgeries has been steady, showing little variation in the six years presented. All these surgeries can occur in the COT, composed by one OT with five ORs and in a few peripheral ORs, as detailed in Subsection 2.2.2.

2.2 Central Operating Theatres' Physical Structure

In this section, the physical plant of HSM and HESE OTs, as well as the surgical specialities performed in each one are described in Subsections 2.2.1 and 2.2.2 respectively.

2.2.1 Physical Structure of COT in HSM

The COT in the HSM is located on the 5^{th} floor. As mentioned earlier, the COT is composed of five OTs, each with two ORs, totalling ten ORs. Moreover, each OT has adjacent rooms to help a continuous, efficient and safe operating process. In Appendix A (Figure A1), it is possible to see the plant of one OT. It is important to denote that all OTs have the same configuration to simplify the process for the involved surgeons and nurses. Apart from two ORs, there are two disinfection areas, one for each OR, an interchange area, one decontamination room, a working, and a material's storage room. Each patient that undergoes surgery enters the OT through the interchange area and is then sent to the respective OR A or B. Outside the OTs, there is also a material's storage room, shared by all ORs, with the necessary provisions.

Each OR from the COT serves a specific surgical speciality, allowing steadiness to stakeholders and reducing the transport of specific material and equipment between different rooms. From ten ORs, six are assigned for elective surgeries: OT 1 for orthopedy; OT 2 for general surgery; OT 3 for vascular surgery (OR A) and urology (OR B); and OTs 4 and 5 are dedicated to emergencies and gynaecology, respectively.

2.2.2 Physical Structure of COT in HESE

The COT of the HESE is located in the new area of the Espírito Santo building. It consists of five ORs (being OR 5 a smaller one), a working area and a post-anaesthesia care unit (PACU) as observed in Appendix A (Figure A2). Although having pre-defined specialities, unlike HSM that has only one speciality per room, each OR can serve more than one in HESE. As stated in Subsection 2.1.3, the surgical specialities are general surgery, orthopaedics, urology, ophthalmology, plastic surgery, paediatric surgery, OTR and stomatology. In this case OR 3 is dedicated to urgencies and OTR surgeries. OR 4 is dedicated exclusively to orthopaedics, while OR 5 is held for ophthalmology interventions. All other surgical specialities are performed in OR 1 and 2. The allocation of specialities to the existing ORs will be discussed further in Subsection 2.3.4.

Besides the COT, the hospital has also one child and maternal OT for gynaecology and obstetrics with a specific PACU, and other ORs where cardio-, gastro- and vascular surgeries are performed.

2.3 Planning and Scheduling

In order to understand the operational process of planning and scheduling a surgery, namely in CHLN and HESE, it is necessary to understand the types of patients that exist, as different types of patients (e.g. elective or non-elective) have different planning and scheduling processes. Those types are described in a patient classification scheme in Subsection 2.3.1. Subsection 2.3.2 describes the path of the surgical patient. Subsections 2.3.3 and 2.3.4 discusses the current surgery scheduling process at CHLN and HESE, respectively.

2.3.1 Patient Classification

In Zhu et al. (2019**)**, two categories are used for patient classification – the type of admission, defining elective and non-elective patients, and length of stay, portraying inpatient and outpatient.

Type of admission

In hospitals, two main classes are considered related to the type of admission of a patient, namely elective and non-elective. On the one hand, elective patients are patients who do not require immediate treatment and therefore are registered in a waiting list. In Portugal, the list is officially named *Lista de Inscritos para Cirurgia* (LIC) and is managed in a centralized way by the waiting list management system, in Portuguese *Sistema Integrado de Gestão de Inscritos para Cirurgia* (SIGIC), under the supervision of CAHS. Although they do not need immediate surgery, the prioritization in the waiting list varies according to the diagnosis, with a defined maximum response time for each type (Portaria n.º 153/2017, de 04 de Maio). On the other hand, non-elective patients are those who require unexpected surgery. Depending on how immediately the treatment is needed, non-elective patients can be divided into two different classes – emergency and urgent patients. Emergency patients require immediate surgery, and any delay can be critical or even fatal. Urgent patients, known in Portugal as *Urgência Diferida*, even though requiring surgery, can be postponed within a closed time window.

Length of stay

After being submitted to surgery, a patient needs to be in the hospital for a certain period. Depending on the length of stay, in nights, an elective patient can be considered an outpatient or inpatient. Outpatient surgery, commonly known as ambulatory surgery is defined when there is the expectation that the patient will stay in the hospital only on that day and does not require to stay overnight. If the patient stays overnight but less than 24 hours in the hospital, it is called an ambulatory surgery with an overnight stay. Outpatient surgeries are usually lower risk surgeries. On the other hand, every surgery that requires the patient to stay more than 24 hours at the hospital is called an inpatient surgery. This type of surgery is harder to manage when considering all stakeholders involved, as there is a need for coordination with the number of ward beds, intensive or intermediate care units, personal and strict pre-operative and post-operative procedures.

2.3.2 Surgery Process in SNS

According to ACSS (2011), the process of surgery episode management is divided into five main stages: referencing, proposal, execution, follow up and conclusion, and it is standardized for all public hospitals. The first stage (referencing) starts once the patient is referenced from an external consultation to a speciality consultation. This external consultation can either be in the same hospital or any other SNS service and is normally asked by the patient. Following this, the request must be accepted by the speciality and the maximum time between the external consultation and the execution of the first speciality consultation is established by Portaria n.º 153/2017, de 04 de Maio according to a provisory identified clinical priority.

With the first consultation the stage of proposal begins which includes all events until the admission for the execution of surgery. Although multiple scenarios for the proposal stage are provided by law, such as transference of the patient to another hospital or refusal of the surgery by the patient, those fall outside the scope of this work and in this section only the patient's normal path will be taken into consideration. Firstly, a care plan with an established surgical intervention strategy is developed by the responsible physician to address the patient's problem. When starting the care plan, the patient is pre-registered in the LIC and the waiting time starts. From here, there are maximum guaranteed response times, *tempo máximo de resposta garantido* (TMRG) established to perform the surgery (Portaria n.º 153/2017 de 04 de Maio). On the registration process, the clinical priority is defined by the doctor in accordance with the illness itself, related problems and severity, base pathology, among other factors (cf. n. 34 of the regulation of SIGIC, published in Portaria n.º 45/2008 de 15 de Janeiro).

Once the patient and the responsible physician for the surgical service accept the care plan, the patient is definitely registered in the LIC and has to wait until the surgery is scheduled. As seen on Table 5, depending on the patient's clinical priority and pathology group, different times apply. The clinical priority varies from 1 to 4 and the pathology group is classified as "general", "oncology" and "cardiology" groups. These times refer not only to the TMRG but also, maximum surgery booking time and minimal advance notice for the surgery for each priority.

Table 5 – Types of priority per pathology and respective deadlines (from Portaria n.º 153/2017 de 4 de Maio)

Clinical priority	Pathology group	TMRG	Maximum time for scheduling	Days in advance for patient notification
1	General	180 days	135 days	20 days
1	Cardiology	90 days	67 days	20 days
1	Oncology	60 days	45 days	20 days
2	General	60 days	30 days	10 days
2	Cardiology/Oncology	45 days	23 days	10 days
3	Gen/Cardio/Oncology	15 days	5 days	5 days
4	Gen/Oncology	72 hours	When possible	When possible

At an operational level, patients are scheduled firstly according to their priority level, and if two patients have the same priority, antiquity in the list shall be considered, with the one who has been in LIC the longest having a higher priority (First-In-First-Out strategy for the same clinical priority). Following the guidelines, hospitals must schedule patients in the hospital's informatics system, in Portuguese *sistema de informação hospitalar* (SIH), at least two times per week, having into consideration maximum surgery scheduling time. After accepting the proposed day for the surgery, complementary examinations, pre-anaesthesia evaluation, and other appointments, when needed, shall be arranged. All these procedures belong to the proposal phase.

The first critical event ends the proposal stage and starts the stage of execution. Critical events are defined as any event from the admission for surgery until medical discharge (ACSS 2011). In the case of medical complications and the need to perform new immediate surgeries, they are also part of critical events.

On the day of the surgery, the patient is asked to arrive at the hospital early that morning. The only exception is for the first surgery of the day, to which the patient is often required to arrive in the previous evening. Once arrived at the hospital, the admission process begins with the completion of an established form. The physician must, in this phase, inform once again the patient of all procedures, objectives, consequences, associated risks, and short- and long-term side effects (cf. the *Carta dos Direitos e Deveres dos Doentes*, published in Portaria n.º 153/2017, de 04 de Maio). At this moment, the enrolment in the LIC is removed and the registration of the surgery must be made in the hospital's informatics system. In the process, all surgery details must be recorded, such as predicted duration, type and procedures, the composition of the team, destination after the surgery and other relevant information described in ACSS (2011).

The surgery team is composed of:

- A 1st surgeon, responsible for the surgery. If the 1st surgeon is an intern, the 2nd surgeon must be a registered specialist, assigned as chief-of-surgery-team;
- A 2nd surgeon;
- Other surgeons if needed;
- One anaesthesiologist;
- One instrument nurse;
- One non-sterile nurse, also described as a circulating nurse;
- One anaesthetist nurse;
- Other participants are allowed when needed.

A report of the surgery must be done as soon as possible, once it has ended. It is recommended to be completed immediately after but there is a limit of 10 days from the surgery day to complete it.

After the surgery, the patient is sent to a PACU and then to a recovery unit. As mentioned before, depending on the type of patient – outpatient or inpatient – the path taken after the surgery will differ.

When the responsible surgeon considers the patient ready to be sent home, a medical discharge is issued for the patient, ending the stage of execution.

The fourth stage, follow-up or *catamnesis*, consists of monitoring the surgical treatment to the patient and should include all follow-up events foreseen in the care plan. It starts with the first consultation after the medical discharge. It should last at most two months and allows the evaluation of the patient and his progression, and the necessity of any other action, not considered in the original care plan. If all events follow the expected path, the last stage of conclusion arises, after the last follow-up consultation. In this stage, the complete clinical process is submitted, along with a conclusion report containing all needed information. The process of elective surgery is then concluded.

Despite being a regulated process, and without compromising any SIGIC rule, each hospital has the independence to manage its LIC and the scheduling of patients, to have a more efficient management of the operating times of its OT. Furthermore, to maintain an adequate level of surgical production, the CAHS establishes with each hospital, the values of annual surgical production. The payment of these surgeries is done *a priori*, prospectively, based on the historical activity costs. This only refers to surgeries scheduled in the correct shifts or slots, known as normal production. To overcome situations when normal production is not sufficient to face the demand, i.e. when there is a need to improve the number of surgeries and thus reduce the waiting list, there is the possibility for additional production outside the regular time windows, in after-hours. This type of surgery is paid per act (fee-for-service) in a retrospective manner by the hospital's RHA and approximately half this payment goes for the hospital and the other half to the surgical team.

The following subsections provide information on patient scheduling at CHLN (HSM) and HESE.

2.3.3 Planning and Scheduling at CHLN

In CHLN, all specialities have autonomy over the scheduling process. This means that in order to book patients, each surgical speciality draws its own schedule. Every head of service shall check the LIC and create the surgical production plan. The booking process is done cyclically in periods of one week. Finally, the week's schedule must then be presented do the COT's director, with at least one week in advance. When scheduling, the head of service has to have into consideration the available time blocks for the respective speciality in each OR. These blocks are part of a schedule defined for a medium- to long-term window called Master Surgery Schedule (MSS). The current MSS is shown in Table 6 for the four OTs from HSM's COT under study. The MSS used in CHLN is often in use for one year, with a monthly periodic review to adjust to personnel capacity variation. Once the end of the MSS year approaches, a broader review is performed to adjust to the more recent strategic objectives.

Although the COT operating hours are established from Monday to Friday, from 8 a.m. until 8 p.m., each speciality has a specific working time, starting usually all surgeries at 8:30 a.m. and with finishing times dependent on the week day as seen in Table 6. The only exception is OT 4, reserved for emergencies and are therefore opened 24/7. Weekdays are divided into two shifts, the first from 8:00 a.m. to 3 p.m. and the second from 3:00 p.m. till 8:00 p.m. As seen on table 6 only OT 2 – OR A and OT 3 – OR B use both shifts. Ramos (2018) points that the reason, according to surgeons' feedback, for ending surgeries at 3 p.m. and do not take full advantage of the full COT working hours in most days is mainly related with the anaesthesiologist's shortage. In the case of HSM, Saturday is the day reserved for additional production.

Table 6 – Master surgery schedule from HSM COT

		OT 1		OT 2		OT 3		OT 4	
		OR A	**OR B**	**OR A**	**OR B**	**OR A**	**OR B**	**OR A**	**OR B**
Mon	8:00 a.m. 3:00 p.m.	Orthopedy	Orthopedy	General	General	Vascular	Urology	Emergency	
	3:00 p.m. 8:00 p.m.			General			Urology		
Tue	8:00 a.m. 3:00 p.m.	Orthopedy	Orthopedy	General	General	Vascular	Urology		
	3:00 p.m. 8:00 p.m.			General			Urology		
Wed	8:00 a.m. 3:00 p.m.	Orthopedy	Orthopedy	General	General	Vascular	Urology		
	3:00 p.m. 8:00 p.m.			General			Urology		
Thu	8:00 a.m. 3:00 p.m.	Orthopedy	Orthopedy	General	General	Vascular	Urology		
	3:00 p.m. 8:00 p.m.			General			Urology		
Fri	8:00 a.m. 3:00 p.m.	Orthopedy	Orthopedy	General	General	Vascular	Urology		
	3:00 p.m. 8:00 p.m.			General			Urology		
Sat									
Sun									

2.3.4 Planning and Scheduling at HESE

As occurs in the planning at CHLN, each surgical speciality is responsible for the management of the waiting list of patients registered in that speciality. In HESE, this scheduling is done monthly by each head of service. When booking, the head of service has to respect the hospital's COT available blocks. These blocks are defined in the MSS (Table 7). The COT is opened during the weekdays from 8 a.m. to 8 p.m., divided into two shifts of 6 hours each, from 8 a.m. to 2 p.m. and from 2 p.m. to 8 p.m.. The exceptions are made in the case of ophthalmology, since OR 5 is closed on Fridays and for urgencies. ORs with blocks reserved for urgencies are opened from 00:00 a.m. until 2:00 p.m. if it corresponds to the first shift or from 2:00 p.m. to 00:00 a.m. if it corresponds to the second shift.

Table 7 – Master surgery schedule from HESE COT

		OR 1	OR 2	OR 3	OR 4	OR 5
Mon	8:00 a.m. 2:00 p.m.	General	Orthopedy	Emergency	Orthopedy	Ophthalmology
	2:00 p.m. 8:00 p.m.	General	General			
Tue	8:00 a.m. 2:00 p.m.	General	General	Emergency	Orthopedy	Ophthalmology
	2:00 p.m. 8:00 p.m.	General	Plastic surgery			Ophthalmology
Wed	8:00 a.m. 2:00 p.m.	Orthopedy	Orthopedy	Emergency	Orthopedy	Ophthalmology
	2:00 p.m. 8:00 p.m.	General	Emergency	OTR		
Thu	8:00 a.m. 2:00 p.m.	General	General	Emergency	Orthopedy	Ophthalmology
	2:00 p.m. 8:00 p.m.	Emergency	Urology	OTR		
Fri	8:00 a.m. 2:00 p.m.	General	Stomatology	Emergency	Orthopedy	
	2:00 p.m. 8:00 p.m.					
Sat		Emergency				
Sun		Emergency				

The empty blocks that can be seen in the MSS are used when required for additional production. By contrast to the procedures in HSM where additional production takes place only on Saturdays, in HESE, the surgeries performed in additional production are done in the empty blocks or afternoon cancelled blocks and Saturdays. Furthermore HESE performs additional production surgeries every other Sunday. The Sundays in-between are used to do a major OT cleanse, required every 15 days. The same rules of financing are applied to HESE and the surgeries in this regime are disbursed in retrospect, as pay per act or fee for service.

2.4 Stakeholders and Operating Theatre Performance

Being a complex procedure, highly regulated, and with the need for elevated expertise in different areas, multiple stakeholders are involved in the process of a surgery. As each stakeholder has different roles, objectives and goals regarding surgery and the surgery planning process, it is essential to define all those stakeholders. Being so, Subsection 2.4.1 describes the main stakeholders involved in the process and Subsection 2.4.2 addresses KPIs regarding different stakeholders.

2.4.1 Main Surgery Stakeholders

Described in Penedo et al. (2015), all OT procedures require multidisciplinary teams, the availability of human resources and their correct management. Although patients and surgeons are accounted as the main stakeholder in most literature, the surgery depends also on anaesthesiologists, nurses, auxiliary staff and others:

Patient: According to the SNS, all health activities must be centred on the patient, and that also applies to the surgery process. While having little or no knowledge and expertise on the matters of surgery, the patient needs to be informed of all procedures he will go through and to give his consent. The type of surgery and thus, the time the surgery takes depend on the patient's pathology and characteristics, as well as the number and speciality of the required physicians. Furthermore, the surgery schedule can suffer disruptions if the patient cancels a surgery or arrives at the OT with delay.

Surgeon: The surgeon is the physician responsible for performing surgery, being the procedure's outcome highly dependent on the surgeon's expertise. This makes him one of the main stakeholders in the process of surgery execution as well as in its planning and scheduling. In fact, he concentrates most of the decision-making powers during the surgical procedure, and in the scheduling process, playing key roles in the whole process. In hospitals, the estimation of surgery duration time is dependent on the surgeon's judgement, and has a great impact on the utilization of the OR. Surgeons have a high degree of specialization and both the 1st and 2nd surgeons present in each surgery must have all the necessary knowledge and information about the clinical condition of the patient they operate. Nevertheless, even though these physicians are the most specialized stakeholders in the surgery context, they also rely on the work of anaesthesiologists, nurses and auxiliary staff to efficiently perform the surgery.

Anaesthesiologist: Anaesthesiologists are physicians responsible for the administration of anaesthesia to each patient undergoing surgery. Their expertise is needed not only to administrate anaesthesia but also to choose the correct type of anaesthesia depending on the surgery procedure and patient characteristics. The presence of these physicians is likewise required during the entire surgery to monitor the patient's stability and if necessary, after it is completed, until the patient has awakened. It is recommended that one anaesthesiologist only supervises one patient at a time (Ordem dos Médicos 2007). Also, it is expected that at least 50% of the anaesthesiologist working time will be allocated to the OT (Penedo et al. 2015).

The scarcity of these professionals is a factor with high impact on surgical production. In 2017 there was a shortage of 541 anaesthesiologists when compared with the needed value in SNS hospitals so extra-hours or freelancing contracts were not required (Ordem dos Médicos 2017). This value is a sum of the provided by each hospital's Anaesthesiologist Service Director and is based on the number of extra hours required and the needed anaesthesiologists' freelancers to face the actual demand. In CHLN, the reduced operating hours on the ORs is mainly related to this factor, as well as in HESE. Penedo et al. (2015) points to the fact that, in HESE, surgeons and ORs could be more utilized if there were sufficient anaesthesiologist, also emphasizing their shortage. In total there are 49 anaesthesiologists in CHLN and 13 in HESE, and a deficit of 100% and 53.8% respectively (Ordem dos Médicos 2017).

Nurses: The presence of nurses is extremely important during the preoperative, perioperative, and postoperative stages. Preoperative nurses are responsible for preparing the patients for surgery and guide them to the OT, while perioperative nurses are required during the surgery and postoperative nurses help and monitor the patients after the surgery. Having the perioperative nurses a much larger impact in the surgery planning and scheduling in comparison with the others, in this work we consider only perioperative nurses as stakeholders. In any surgery in SNS, it is required the presence of three nurses with different areas of expertise, namely the instrument nurse, who is responsible for preparing the OR with the needed material and handling the sterile equipment to the surgeons, the circulating nurse with the responsibility of receiving non-sterile material from surgeons and its handling, and finally, an anaesthetist nurse, accountable for supporting the anaesthesiologist with all the required help. All OR nurses are expected to have 100% of their time allocated to the OT (Penedo et al. 2015).

Auxiliary and technical staff: Despite playing a smaller role in the surgical procedure itself, auxiliary and technical staff is crucial for running an OT operation. To have an OR available for surgery, there is a need to clean and prepare the room for the surgeon's procedure. Auxiliary staff are responsible for these procedures and highly influence the turnover time, or time between surgeries, which starts when a patient leaves the OR and ends when the OR is ready to receive a new patient. Additionally, when there is a need to operate special devices or technologies, such as endoscopic cameras or echocardiograms, during the surgery or prepare them for surgeons or nurses, technical staff is required.

OR Manager: At last, the OR managers, that in both CHLN and HESE cases, are COT managers, are responsible for the correct management of all ORs in the COT. They are responsible to allocate each time block to a surgical speciality or team, receive all booking proposals and cross-check with all other departments, namely nurse, auxiliary and technical staff and post-surgery areas, if there is the availability of both human and physical resources. If all essential resources are available, the OR manager has to inform all parties involved.

2.4.2 Objectives and Performance Indicators

Individual preferences of different stakeholders are sometimes conflictive, and trade-offs must be done in the hospital, to reach a defined OR schedule. The gap between this defined schedule and an optimal one has not been studied in the SNS, mainly because little work has been done in accessing the expected production and optimal schedule with the current productive factors. For that reason, continuous monitoring of the overall performance of the OT is not applied in SNS hospitals. In practice, schedules are proposed by each surgical speciality or surgeon, which leads to non-standardized procedures and choices that are almost entirely dependent on the decision maker's perspective.

In 2013, through Despacho n.º 4321/2013, the Ministry of Health created a working group to carry out the first study on the subject of evaluating the OT's situation in Portugal. The main objective of this team is to assess the OTs with respect to their physical capacity, human resources, production, and quality. As a result, the 2015's Assessment of the National Situation of OTs - Penedo et al. (2015) has been published. In this work, performance indicators were created to evaluate the quality, production, and productivity of each OT. These indicators have been designed with the help of a multi-disciplinary team and were considered suitable to give a complete evaluation. Currently, this is still the only national assessment of OTs and therefore most performance indicators used in this thesis are extracted from this work. From the list of indicators, the most important performance indicators to this work were selected and are presented in Appendix B (Table B1).

To organize the indicators, they are divided into three groups, namely Quality, Production and Productivity. Quality is mainly associated with the service delivered to the patients, mainly measured in a function of waiting time. Patients, as an essential stakeholder, expect to have minimal waiting time possible, which is a consequence of a good OT planning and scheduling. The percentage of operated patients within the maximum waiting time – TMRG – and the mean and median patient's waiting time are the indicators studied in this quality group. To address production, the main indicators relate to the number of both elective and non-elective surgeries, and the usage time of each OR as well as the time of OR preparation for a patient's surgery. These production metrics are very important mainly to hospital managers, who have to report to each RHA their results in order to comply with the contract between the hospital, the respective RHA and CAHS. Finally, the productivity group, although closely related to production, considers the resources used to achieve that production and how well they are employed. These indicators closely relate to each stakeholder, measuring the utilization rates of surgical specialities or surgical groups, nurses and also anaesthesiologists. Productivity indicators are also used to evaluate the production per OR and block.

According to these parameters (Table B1), in 2015, the study revealed that improvement could be achieved. It was stated that CHLN had the potential to increase the OR availability and improve the low productivity of each OR. The study recommended a higher utilization rate of surgeons as well in HESE.

2.5 Problem Definition

The process of scheduling patients is, as mentioned, performed by each surgeon or head of speciality manually. To help the scheduling process, SNS hospital's provide software, which permits visualizing the ORs' schedule and book new surgeries. The booking itself, however, is still done by hand where the main judgement is the surgeon's one, and no optimization is sought. This method allows time misjudgements that lead to both under- and overestimation of cases per slot. In cases of underestimation, the OR's capacity is not fully used. In the scenario of overestimation, patients whose surgery is not performed until the end of the block, have their surgery cancelled and postponed. This generates a high dissatisfaction among patients.

To address the problem of case misjudgements that lead to non-optimized solutions, as mentioned in the first chapter, the optimization of ORs has been studied for several years in academic research. Although the common goal is towards optimization, OR literature can be divided into three decision levels (Cardoen, Demeulemeester, and Beliën 2010), namely strategic in long-term level, tactical for medium-term and operational in short-term. Strategic and tactical decisions aim, from long- to medium-term, at speciality capacity planning, human resources distribution, surgery forecast, allocation of teams, and creating cyclic schedules or MSSs. Operational decisions are centred in scheduling patients from a waiting list to a specific day and starting time. This optimization is usually divided into two phases, advance scheduling, also addressed as surgical case assignment, where patients are assigned a specific day and an OR, and allocation scheduling, where it is decided the exact starting time of each surgery. The division is presented with further detail in Chapter 3, in the literature review.

Even though most academic work regarding OR optimization is focused on the operational decision level (Zhu et al. 2019), their application in hospital scenarios is almost inexistent and the surgery scheduling of patients is still performed manually by surgeons. Most papers propose single or multi-objective models, but do not integrate all real-life specifications from hospitals, focusing on some areas over others. Furthermore, the output quality of each research is not directly comparable with other models, mainly because the instances used differ, and the models' objective function are different.

This study proposes a benchmark of selected models available in the literature, by using the same instances, collected from CHLN and HESE. The focus is done on the advance scheduling problem, since an optimized case assignment leads to the decrease of under- and overutilization of resources, leading to less cancelations and sequentially, a higher patient satisfaction. For that reason and to evaluate the obtained solutions, a matrix composed of indicators that have priority to SNS is created. By using this evaluation method and the same instances in all models, it is implied that models with a higher overall score in the benchmark are more suitable for daily hospital utilization, at least, in the SNS.

2.6 Chapter Conclusions

The process of planning a surgery, since the patient has the first consultation and until the medical discharge, is extensive and depends on several different stakeholders. Despite studies performed and the creation of a working group to carry out the first study on the subject of evaluating the OT's situation in Portugal in 2013, there is still much that can be done towards a better process in OT planning and scheduling. In fact, the creation of indicators, used in 2015 (Penedo et al. 2015) to assess the OT's situation, showed that there was space to improvement.

With the understanding of the underlying problem regarding inefficiency in OR planning and scheduling, the focus of this work is set on the advance scheduling problem of the operational decision level to schedule patients to a certain OR and day, both in CHLN and HESE.

In the following chapter, a literature review is discussed. As this work addresses the operational decision level of OR planning, the review is focused on academic research on OR planning and scheduling optimization models and with more detailed, in the operational decision level.

3 Literature Review

This chapter presents a deep review of the literature on the OR planning and scheduling problem. As mentioned in Chapter 2, this work and the problem under study are focused on the operational decision level and thus, the literature review is dedicated to understanding the current state-of-the-art on OR planning and scheduling only at an operational level.

Considering all academic research on the topic, a search approach is defined to select the literature discussed in this chapter. The references cited in the most recent survey on OR planning and scheduling (Zhu et al., 2019) is used as baseline. Furthermore, since more scientific papers were published in the meanwhile, a search was performed in databases such as ScienceDirect, B-on, IEEE and Web of Science, using keywords “operating room”, “surgery”, “planning and scheduling” in the title, abstract and keywords. Following this methodology, 118 papers are discussed in this literature review: 95 obtained from Zhu et al. (2019) and 23 from additional search.

Section 3.1 describes the framework used to analyse the papers. Following the framework structure, Section 3.2 specifies different levels within the operational decision level, Section 3.3 presents patients characteristics, Section 3.4 considers scheduling strategies and Section 3.5 discusses problem features. Finally, Section 3.6 concludes the chapter.

3.1 Selecting a Framework

Most literature reviews focus on the hierarchical division between long-term, medium-term, and short-term decisions. Guerriero and Guido (2011) use a framework with those levels of decision and this division is phrased as strategic, tactical, and operational decision levels, respectively. The same hierarchical division is taken in Abdelrasol, Harraz, and Eltawil (2014) but the delimitation of each level is better defined, as the long-term level accounts for the case-mix problem, the medium-term for the MSS problem and the short-term decision accounts for the surgery scheduling problem. As such, this leads to papers that do not fit into this strict classification scheme (Samudra et al. 2016). To prevent this limitation in categorization, Cardoen, Demeulemeester, and Beliën (2010) propose the idea of descriptive fields with six different fields to classify each problem under study. Zhu et al. (2019), although considering the hierarchical levels as a parameter, follows the concept of fields proposed by Cardoen et al. (2010) and improves their model by rearranging and adding some other descriptive fields, namely decision level, scheduling strategy, patient characteristics, problem features – including uncertainty, objective functions, certain requirements and multiple stages –, mathematical models, and solutions and methods.

In this work, a similar concept of fields, based on Zhu et al. (2019), is developed to address all needed characteristics of the thesis. The organization of the literature is made in four domains that correspond to the following sections:

- Decision Levels (Section 3.2) – as the literature review in this work concerns only the short-term – operational – decision level, this section divides the papers into advance scheduling, allocation scheduling and the integration of both.

- Patient Characteristics (Section 3.3) – the review is made between elective and non-elective patients. The category on elective patients is further divided into in- and outpatients, and the category of non-elective patients is further divided in emergency and urgency patients.
- Scheduling Strategies (Section 3.4) – this section analyses the literature in terms of the concepts of block strategy, open strategy, and modified block strategy.
- Problem Features (Section 3.5) – this field considers the uncertainty present in each studied model. Furthermore, it also encompasses the level of integration of the problem as well as objective functions.

In Appendix C, a summary of the literature review performed is presented (Table C1), classifying all the reviewed papers according to the criteria followed in this framework.

3.2 Decision Levels

The operational decision level regards short term decisions involving selecting cases from a patient or surgery case list, assign a surgery date, OR and a starting time. This level can also be referred to as the surgery scheduling problem (SSP) (Abdelrasol et al. 2014). While the set of needed resources for each surgery (e.g. surgeons, nurses, material resources) is usually defined *a priori* in a previous stage of decision, by assigning them to a block in an OR, some authors assign those resources simultaneously with the SSP. For example, some authors consider the integration of nurse and surgery scheduling (Beliën and Demeulemeester 2008; Guo et al. 2016) or the surgeon rostering problem (Van Huele and Vanhoucke 2014).

The operational decision level is often decomposed in two phases, namely advance scheduling and allocation scheduling. Advance scheduling consists of selecting the patient or surgery case from a waiting list and assign the patient to a specific day and OR. In the allocation scheduling, from the list of cases selected in the former phase, a starting time or sequence of surgeries is established. Subsections 3.2.1 and 3.2.2 discuss the papers focused on advance and allocation scheduling, respectively, while Subsection 3.2.3 introduces the ones that integrate these two phases.

3.2.1 Advance Scheduling

Advance scheduling consists of selecting the cases from a set of patients registered in a waiting list, assigning an OR and a specific day within a defined planning horizon. This planning horizon varies mostly from a few days to a few weeks. Although some authors propose a flexible planning horizon (Ceschia and Schaerf 2016), most use a static planning horizon. The OR utilization is extended in Roshanaei, Luong, Aleman, & Urbach (2017a) by selecting patients to be collaboratively scheduled across a network of hospitals with different MSSs for their ORs. Also, the list of patients to schedule consists of mandatory patients and optional patients, where a threshold is previously defined to divide mandatory and optional patients in such a way to guarantee enough resources for all mandatory patients.

Agnetis et al. (2014) decompose the approach in two separated phases. Firstly, assigns different surgical specialities to the available sessions in different ORs, creating a weekly MSS (tactical decision level), and then allocating elective cases from a waiting list to the sessions (operational decision level). Similarly, Moosavi & Ebrahimnejad (2020) constructs the MSS and selects elective patients to operate although integrating emergency demand and introducing a *complete opening policy* to choose which ORs to open or close during the planning horizon.

When selecting elective patients from the waiting list, most authors consider a priority score which prioritizes patients according to the urgency of surgery and the waiting time (Min and Yih 2010a; Testi, Tanfani, and Torre 2007; Valente et al. 2009). On the one hand, each urgency of surgery, defined by the surgeon, has a determined due date and the sorting of patients is done through the earliest due date. On the other hand, the waiting time accounts for the time since the patient is proposed to surgery and the prioritization is given by a first-come-first-served (FCFS) policy. This model is akin to what is performed in SNS. In Marques & Captivo (2017), three different models with different selecting rules are used, according to the points of view of the administration, the surgeons, and a mixed model to best suit both. The authors segment the problem, selecting first the patients within the waiting list and then assigning those patients a day, a time block and an OR. Aida Jebali & Diabat (2015) present a situation where the admission date of a patient is already scheduled but due to a trade-off between the efficient hospital's resource management and patient-related costs, the surgery can be postponed and thus the admission date can change. This online re-scheduling is used to minimize the overall cost of the OT.

In several studies, when selecting patients, the relation between the patient and the surgeon is pre-established and the patient is allocated to a block assigned to the corresponding surgeon (Guido and Conforti 2017; Roshanaei et al. 2017b; Tan et al. 2011). Molina-Pariente, Torres, & Cia (2009) studies an elective case scheduling problem by analysing two policies of surgery scheduling, namely assigning a patient to a surgeon and then the tuple is assigned to an OR, or the inverse situation where a patient is assigned to an OR and then a surgeon is allocated to the tuple. The authors point out that the latter allows more flexibility than the former, although being more difficult to implement due to the patient's preferences in having surgery with the surgeons that followed the case and vice-versa.

In the advance scheduling, the set of scheduled patients is a subset of the eligible patients since not all patients are scheduled in most cases. To maximize the number of scheduled patients, or to deal with possible stochasticity, some papers allow overtime (Addis, Carello, and Tànfani 2014; Astaraky and Patrick 2015; Lamiri et al. 2007; Rachuba and Werners 2017), even though most research does not allow overtime when addressing the problem. In the allocation scheduling problem, described in the next section, the set of scheduled patients to a specific day, OR or block is supposed to be already defined focusing the decision on the sequence or starting time of those surgeries.

3.2.2 Allocation Scheduling

The range of characteristics and decisions discussed in the allocation scheduling can vary between authors (Cardoen et al. 2010). The literature reviews of Magerlein & Martin (1978) and Samudra et al. (2016) consider that the allocation schedule comprises the integration of the decision on the OR selection and the sequencing or starting time definition for each surgery in a daily list defined *a priori* with the cases for the day. In turn, Guerriero & Guido (2011) and Zhu et al. (2019) consider only the starting time or sequence definition to each individual surgery. Castro & Marques (2015) develop a two-phased model, first to assign surgeries to ORs and then to schedule surgeries in each OR so that surgeons can operate in different ORs without overlapping cases. Apart from surgeons, the nurse rostering problem to schedule nurses to shifts based on surgery production throughout the day is introduced in Bilgin et al. (2012). In its original scheme, the allocation schedule resembles a multiple parallel machine scheduling problem where a set of tasks (patients or surgeries selected in the advance scheduling phase) have to be scheduled to one machine (OR) or sequenced in a given machine.

When sequencing patients, Hamid et al. (2019) state that the setup-time for each individual surgery is dependent on the sequence, mainly in the scheduling of open-heart surgeries that imply longer times and more critical conditions. The model is used to define the number of open-heart surgeries and its sequence and then to estimate the number of ICU beds required based on the number of surgeries and the length of stay of each patient. The study of different sequencing rules has been investigated by few authors (Liang et al., 2015; Marcon & Dexter, 2006; Testi et al., 2007). Testi et al. (2007) use simulation to validate an MSS developed in an earlier phase and analyse longest waiting time, longest processing time and shortest processing time sequencing rules. Marcon & Dexter (2006) also study different sequencing rules in a means to smooth the flow of patients entering the PACU and thus reducing peaks of post-surgery resource utilization. Among the seven used rules (random, longest cases first, shortest cases first, Johnson rule, half increase and half decrease, half decrease and half increase, and mix rule), the authors advise against the use of the longest cases first since it creates a large discrepancy of throughput through the day. In another research, instead of testing how different simple rules perform, Liang et al. (2015) test a scene-based combination of three sequencing rules – FCFS, shortest processing time and earliest due date –, by interchanging them during the planning horizon. Furthermore, the authors study a linear weighted combination on these three rules to compose one combined rule that maximizes the patient throughput and minimizes patient waiting time.

Kong, Lee, Teo, & Zheng (2013) and Khaniyev, Kayış, & Güllü (2020) focus on assigning starting times for each surgery, considering a given number and sequence of surgeries with uncertain duration so to reduce the waiting time of patients, overtime usage and room idle time. Few authors do an online redefinition of the starting times of surgeries based on the arrival of unexpected emergencies. Erdogan & Denton (2013) develop two models, namely dynamic appointment scheduling where the arrival of new non-elective patients is stochastic but limited to the OR capacity and second one, Appointment Scheduling in the Presence of No-Shows, where the case of elective patients not showing for surgery without prior notice is taken into consideration.

3.2.3 Integration of Advance and Allocation Scheduling

The integration of both advance and allocation scheduling problems has also been studied in the literature. The majority of the authors establish a clear distinction between advance and allocation and solve both problems in a stepwise manner. Wang et al. (2015) solve the problem by choosing first which patients can be operated within the planning horizon and the day of surgery, and in a second phase, a sequencing problem based on the two-stage no-wait hybrid flow-shop problem, minimizing the number of OR to open. Saadouli et al. (2014) develop a model to assign operations to a day, an OR and later a sequence for the surgeries under the assumption that a list of pre-selected cases with undetermined duration for the week is known.

Developing and solving both phases in a generalized model allows more optimized solutions, although increasing the problem complexity. After selecting surgeries and assigning them to ORs, Jebali et al. (2006) use two strategies to sequence cases. The first consists in taking the surgeries assigned in the first step and sequence them. The second reconsider the assignment of surgeries to the ORs. The authors stated that the second strategy slightly improves the overall score in the objective function compared with the first, but the computation time is much higher.

Dios et al. (2015) introduce a model to estimate the week for surgical intervention to a low degree of uncertainty in a medium-term, six-month, period. In the short-term, for a period of two weeks, the surgery plan for each day and the OR is constructed, having in consideration necessary resources and patients' availability. Planning surgeries through a longer period allow a better allocation of physical resources and medical staff. For example, a simulation of the operational phase can be used to access the model developed upstream in case-mix problem and the MSS problem (Ma and Demeulemeester 2013).

3.3 Patient Characteristics

Two categories are used to classify patients, namely the type of admission and the length of stay in the hospital. Type of admission distinguishes between elective and non-elective patients. The distinction between both lays in the urgency of surgical treatment (less and more urgent, respectively). The latter can be further split in: non-elective patients who require immediate intervention are also addressed as emergency patients; and non-elective patients whose surgery can be slightly delayed within a determined time window are addressed as urgent patients. The length of stay comprises a partition between patients that are discharged from the hospital within 24 hours following the surgery and the ones who need to stay more than 24 hours in the hospital. The former are outpatients and the latter are inpatients. The following Subsections 3.3.1 and 3.3.2 focus on the type of admission and the length of stay classification, respectively.

3.3.1 Type of Admission – Elective and Non-Elective Patients

Elective patients can be programmed in the medium-term horizon, generally up to half or one year. This antecedence and foreseeability of demand allows a better organization of resources and are easier to manage. Non-elective patients are unpredicted and require same- or next-day surgery which increases the scheduler work of fitting all demand in a short planning horizon.

Although some authors do not explicitly refer which type of patient is being studied, most scientific work in this area is targeted at the planning and scheduling of elective patients. Few researchers fundament their choice to disregard non-elective patients, indicating that in the problem under study the ORs are dedicated to elective surgeries exclusively, and non-elective ones are performed in separated ORs (Díaz-López et al. 2018; Dios et al. 2015; Fei, Chu, and Meskens 2009; Guido and Conforti 2017; Hamid et al. 2019; Lamiri, Augusto, and Xie 2008; M'Hallah and Al-Roomi 2014; Rath, Rajaram, and Mahajan

2017; Silva et al. 2015; Testi and Tànfani 2009; Testi et al. 2007; Vali-Siar, Gholami, and Ramezanian 2018; Zhang, Dridi, and El Moudni 2019). The use of predicted capacity is used also by Herring & Herrmann (2012); Aida Jebali & Diabat, (2015); Jebali et al., (2006); Ma & Demeulemeester, (2013); Min & Yih, (2010b) though in a deterministic way by reserving, at a tactical level, capacity of each OR or blocks for emergency cases.

For handling emergency patients three main policies are considered, namely dedicated policy, flexible policy or a combination of both (Ferrand, Magazine, and Rao 2014; Van Riet and Demeulemeester 2015). In a dedicated policy, specific ORs are used for emergencies. As an example, despite scheduling only elective patients, Roshanaei et al. (2017a) state that by minimizing the number of opened elective-oriented ORs, closed ORs can be used for emergencies, thus increasing non-elective capacity. The flexible policy can be further divided into two - insertion policy, that consists in scheduling an emergency case in-between elective cases, and reserved slack, that implies reducing the total capacity of each OR to allow some time, or slack, for emergencies. Kamran et al. (2019) use the notation of predictive disruption management for dedicated and reserved slack policies, and post-disruption management for insertion policies. In Van Essen et al. (2012) an insertion policy of break-in-moments is used. The authors simulate how the waiting time of emergency patients varies with the distribution of those moments. Through a discrete event simulation, Wullink et al. (2007) compare the approach of dedicated ORs versus reserving slacks in elective ORs in a Belgium hospital. The authors state that the latter improves the emergency waiting time, reduces total overtime and improves OR utilization. More recently Duma & Aringhieri (2019) introduced a comparison model between shared and dedicated ORs. Their findings validate the work Wullink et al. (2007), but point to the increase of elective surgery cancelations in ORs shared by elective and non-elective patients.

Few researchers target both elective and urgent patients – non-elective patients whose surgery can be postponed within a defined short-term window. Marques & Captivo (2015, 2017) and Marques et al. (2015) model urgent patients as high-priority elective patients, that must be scheduled in the planning horizon with certain rules. Due to their nature, urgent cases can also be booked as add-ons at the end of the day to improve the OR utilization while minimizing the total overtime and assuring urgent surgeries met the required due date (Pham and Klinkert 2008).

3.3.2 Length of Stay – Inpatients and Outpatients

The distinction amongst inpatient and outpatient (both elective patients) is rarely done in the literature. Nonetheless, the differentiation is important to be made since inpatients, that stay in the hospital for more than one night after the surgery, and outpatients, who are discharged within 24 hours after the surgery, have distinct requirements and interact differently with the system. Guda et al. (2016) consider that unlike inpatients, outpatient surgeries have a probability of starting earlier than expected if the room is already vacant since almost no patient preparation is needed. This results in a decrease of total OR idle time for large sets of outpatient surgeries. In Meskens et al. (2013), alongside with high-priority patients, outpatients should be operated as early as possible. This strategy allows the patient to recover and leave the hospital on the same day without utilizing a bed over-night. Some hospitals even have dedicated ORs for outpatients. Marques et al. (2012a) and Marques & Captivo (2015), due to the structure of the hospital studied, tackle both in- and outpatients, although considering a separate, specific OR only for outpatients.

3.4 Scheduling Strategies

When addressing OR planning and scheduling at an operational level, different scheduling strategies may be employed, namely block, open and modified block scheduling strategies (Marcon and Kharraja 2003). On the one hand, a certain surgeon or surgical speciality can have a predetermined block of time in a certain OR-day. Patients from that speciality or surgeon's waiting list can only be operated in a corresponding assigned block. This strategy is known as block scheduling strategy. On the other hand, open scheduling strategy allows patients to be scheduled in any OR, without assigning specialities to ORs or time blocks. A compromise between both strategies, i.e. modified block strategy, is possible and leads to schedules with a combination of free and reserved blocks. Most literature studies block and open scheduling strategies while modified block scheduling strategy is rarely approached (Zhu et al., 2019).

When considering a block scheduling strategy, Shylo et al (2013) state that if resources shared among specialities are not considered, all speciality's schedules are independent of other specialities. This allows decomposing the surgical case assignment problem in a set of nonoverlapping subproblems, one for each speciality or surgeon (Marques & Captivo 2017). By using a block scheduling strategy, the complexity of the surgical case assignment problem decreases significantly from choosing an open schedule, as the search space decreases. In fact, the block strategy is a particular and simpler case of the open scheduling strategy and any optimal block strategy solution is a feasible solution in the same problem using open scheduling strategy (Fei et al. 2009; Liu, Chu, and Wang 2011).

Marques & Captivo (2015) tackle the assignment of surgical specialities to each OR and later the scheduling of surgeries in those blocks. In their work, simultaneous blocks can be assigned to the same speciality, allowing the surgeon to change and operate in different ORs. Furthermore, in the allocation phase, although the surgery-related time includes the surgery itself and the time for cleaning the room, the surgeon, as soon as the surgery itself ends, is free to operate in other OR assigned to the corresponding speciality. This situation is rarely seen in literature since most papers consider an overall surgery time uniquely that encompasses both surgery time and turnover time (see e.g. Marques et al. (2012a) for an exception). In other works, the number of simultaneous blocks belonging to the same speciality is restricted to level the types of care performed at the same time among the OT (Agnetis et al. 2014). In Agnetis et al. (2014), the authors also specify that some specialities need particular ORs due to special requirements of resources and equipment.

The presence of overtime in particular blocks is also neglected by many researchers, considering only the maximum overall overtime in models. Rachuba & Werners (2017) study an advance scheduling problem having blocks that can incur in overtime which in turn has upper bounds for each OR and each speciality. The authors present a multi-objective problem to minimize the total waiting time, overtime utilization and the number of patient deferrals. In contrasts, most hospitals limit the usage of overtime to certain blocks, e.g. only the afternoon block can use overtime, as any overtime used in the morning block cause delays and possible cancellations in the afternoon cases.

The block strategy lowers the overall OT flexibility but is easier for hospital managers to implement because changing the speciality can lead to higher turnaround times between surgeries. Moreover, a block strategy provides a more stable agenda to surgeons. Abedini et al. (2016) consider an open scheduling strategy with identical ORs and a set of surgeries with a determined speciality associated. In the model, the authors consider a fixed setup-cost whenever two consequent different-speciality surgeries are scheduled in the same OR. Using a bin-packing model, with costs for idle time, regular and overtime, the objective is to minimize the idle time of each OR while maximizing utilization. The cost of idle time is assumed to be equal to the cost of regular time. To decrease the speciality turnaround time, few researchers use a particular case of the open scheduling strategy. It consists in blocking the OR to the speciality of the first surgery assigned for that OR-day (Castro and Marques 2015; Roshanaei et al. 2020). This strategy is very similar to using full-day blocks for surgeries, although the only difference lays in the fact that in the former case, the speciality is not chosen *a priori*. Dios et al. (2015) use an open scheduling strategy to model both advance and allocation scheduling at short to medium-term periods. The authors consider the heterogeneity of ORs and consider the idle time of surgeons between surgeries. To reduce idle time, the maximum number of ORs where a surgeon can operate is settled, thus minimizing long OR commutes. An upper bound is also set on each surgeon daily working time.

A comparative research was performed in Chaabane et al. (2008). The authors developed two methods, one to maximize the number of assigned cases and a second to minimize the surgical case costs, i.e. hospitalization time and overtime, to access both block and open strategies. The results are compliant with what has been previously discussed, stating that open strategies allow more surgical production, although changing successively surgeons and specialities in the same OR may not be realistic for hospitals managers to consider. Being so, the authors highlight that mixing both strategies could be beneficial. Kamran et al. (2018; 2019) opt to develop a modified-block strategy, reserving some bocks for specialities while leaving others open for patients of different specialities. This hypothesis is made under the assumption that all specialities to be scheduled in any open block are fitted to operate in an all-purpose OR, without any special need. The same principle is used in Lamiri et al. (2008), where the authors establish semi-open blocks. These blocks, although assigned to a certain speciality, can have surgeries from other specialities, when there is available capacity, but with a higher cost.

3.5 Problem Features

As examined, each problem studied in the literature has different particularities and unique features. In this work, we follow the concept of Zhu et al. (2019) to organize the literature according to specific features. Their classification has been enhanced in this work by including new degrees of uncertainty (Subsection 3.5.1), a new criterion of vertical and horizontal integration (Subsection 3.5.2) and objective functions (Subsection 3.5.3).

3.5.1 Uncertainty

The OR planning and scheduling problems have an intrinsic nature of uncertainty. Nevertheless, some authors develop a deterministic while others handle the uncertainty nature with stochastic approaches. While the former ignores the uncertainty and unpredictability on the models, the latter tries to comprise uncertainty to a certain degree. Although most researchers do not include uncertainty in the studied problems and choose to develop deterministic models, almost all of those papers state that the future exploration of the problem with stochastic parameters is an important step (Doulabi, Rousseau, and Pesant 2016; Guo et al. 2016; Wang et al. 2015). In OR planning and scheduling various types of uncertainty exist. The presence of multiple phases and stakeholders increase the variability in the process (e.g. surgery duration, postoperative bed availability, nurse availability, surgeon lateness). Five types of uncertainty are identified in this work, namely related with case duration, post-operation length of stay (LOS), elective patient arrival, emergency demand, and lastly resource availability. Table 8 shows the number of papers analysed in this work with deterministic or stochastic approaches and the types of uncertainty tackled. Note that the sum of number of papers addressing each type of uncertainty is greater than the number of papers with stochastic approaches as there are papers that handle more than one type of uncertainty.

Table 8 – Number of papers with deterministic or stochastic approaches and types of uncertainty addressed

	Deterministic approaches	Stochastic approaches	Types of uncertainty				
			Duration	LOS	Elective Arrivals	Emergencies	Resources
No. Papers	52	66	58	16	14	20	7

As can be seen in Table 8, the duration uncertainty has been highly incorporated, in comparison to all other types of uncertainty. Duration uncertainty relates to the unpredictability of the exact duration of surgeries that leads to a possible deviation between the planned and the actual duration of the procedures. This deviation can be caused by multiple factors, from the patient condition, downstream resource shortage that can cause bottlenecks in the OR and influence the surgery duration (Lee and Yih 2014), the surgery type (Jebali and Diabat 2015), the experience of the surgeon performing surgery (Molina-Pariente et al. 2015), and others. The uncertainty in the case duration has a large impact both on under- and overtime that leads to idle time or possible surgery cancellations. Kroer et al. (2018) solve a OR planning problem considering surgery duration uncertainty using data of multiple operations to generate distributions for their length, with the aim of minimizing the number of open ORs and overtime. The problem is solved with 2-Step Relax-and-Fix and All Open Relax-and-Fix heuristics. The authors use simulation to test the heuristics robustness. To estimate the duration of the cases, researchers often use probabilistic distributions, such as lognormal, normal, and gamma. Lognormal distributions are shown to be the most used due to its fitness to real hospital scenarios (Landa et al. 2016; Zhang et al. 2019). In Marcon and Dexter (2006), a lognormal distribution is used to model the OR surgery time and additionally, the PACU case time.

Along with the PACU usage, the usage of resources in all pre-, peri- or postoperative phases also influence the OR normal utilization. When bottlenecks are created, the flow of patients is disrupted, blocking the resources upstream and creating idle times in the downstream resources. Uncertainty in the LOS of each patient after surgery, when few recovery beds are available may lead to OR blocking since patients are not able to be moved from the OR. Still, even when there are enough recovery beds to prevent OR blocking, the LOS has associated costs. In the literature, 16 papers address LOS uncertainty. It is interesting to note that all these papers also address duration uncertainty, concluding that duration uncertainty is more relevant for the stakeholders than the one on LOS. Few authors consider the variance of LOS after the surgery to be dependent on the patient's characteristics and health conditions. Ceschia and Schaerf (2016) tackle an advance scheduling problem for two- and four-weeks scheduling where each patient has an expected LOS but due to individual factors, an overstay risk is modelled to represent the probability of staying more nights than predicted. Thirty large instances up to 1602 patients were generated based on real hospital data and the LOS of each one was then computed using a lognormal distribution. A simulated annealing metaheuristic is used to solve the problem. Instead of using probability distributions with known parameters, robust optimization is also used in literature as an approach to deal with stochasticity (see e.g. Addis et al. (2014); Kong et al., (2013); Marques & Captivo (2017); Moosavi & Ebrahimnejad (2018); Rath et al. (2017)). To deal with the LOS stochasticity Vali-Siar et al. (2018) build a model based on the robust optimization approach by Bertsimas and Sim (2004) due to its risk-averse nature and solve the problem using a genetic algorithm and a constructive heuristic algorithm.

Unpredicted demand or arrival uncertainty is another type of uncertainty in the elective case planning and surgery scheduling. This demand can increase the waiting list of patients in the planning phase when regards new elective demand, or create disruptions in the daily schedule when taking in consideration non-elective arrivals or patients that do not show for surgery. Even though the number of papers focusing on elective arrival uncertainty is relatively lower than those addressing emergency uncertainty, it focuses also on uncertainty and thus is included in this section. When dealing with uncertain demand, representing new arrivals, Poisson distributions are used in most papers (Astaraky and Patrick 2015). The authors present a Markov Decision Process Model to schedule patients in a pre-defined MSS with the objective of reducing patient tardiness, overtime usage and to minimize ward congestion. Booking decisions are discrete and occur once in a day using a Least Squares Approximate Policy Iteration algorithm to simulate a long-term horizon. During the process, the new demand for elective surgery follows a Poisson distribution. Medical discharges from patients no longer requiring surgery are also simulated and follow a binomial distribution. Erdogan and Denton (2013) consider that the duration and number of surgical cases are uncertain due to tardy cancellations and no-shows (i.e. patients who fail to show up for surgery) in a two-stage stochastic linear programming model. Moreover, the authors present an improved multistage stochastic linear programming model to incorporate uncertain add-on cases. All scheduled cases have a patient dependent no-show probability and the add-on patients also have a pre-determined probability. The presence of no-shows is common in outpatient clinics (Lee et al. 2005), creating idle times, resource wastage and underutilization of ORs.

Emergency demand has an intrinsic high-level of uncertainty that leads to OR overutilization if poorly managed. Some authors do not consider non-elective cases, indicating that non-elective cases are dealt with in separate and dedicated ORs. Both reserving ORs uniquely for emergencies or reserving slack in shared OR are known to be predictive-disruption models, in comparison with post-disruption management policies as mentioned in Section 3.3.1. Bruni, Beraldi, and Conforti (2015) study three recourse strategies to complement the weekly scheduling problem and allow emergency surgeries with its stochastic nature. The first one consists in allowing overtime to accommodate all future emergency cases by simply adding those to the normal schedule. The second strategy, swapping recourse, is used to enable elective surgeries to move to another less congested OR if an emergency surgery is being performed in the supposed OR. Lastly, the complete rescheduling strategy may be employed to cancel and postpone surgeries for the next day. Results have shown no dominant solution, with score value varying with the used algorithm, instances sizes and number of ORs. A stochastic programming model is proposed in Lamiri, Xie, Dolgui, et al. (2008) to address the uncertainty in emergency arrivals over a period of one and two weeks. The model considers the capacity required for emergency cases arriving at each moment of the planning horizon as a random variable. Moreover, a Monte Carlo Simulation is used to generate samples and estimate objective function scores. According to the authors, as the number of the samples increases, solutions converge to optimality and outperform deterministic models.

Resource availability is also considered in the literature. Although some researchers incorporate renewable and non-renewable resources in their models (e.g. recovery beds, nurses, and certain surgery-related equipment), most of those integrate the resources in a deterministic manner, while only a few number of authors consider uncertain resources. Molina-Pariente et al. (2015) consider that although patients are assigned to surgeons in advance, the allocation of an assistant surgeon to each surgery is stochastic. According to their model assumptions, as the surgery duration is highly dependent on the assistant surgeon level of expertise, the assignment stochasticity has a non-negligible impact of the objective function’s score. The availability of downstream resources due to uncertain LOS also influence OR utilization. Both Azari-Rad et al. (2014) and Lee and Yih (2014) consider that due to shortage of the certain type of resources downstream, the patient path, regarding recovery beds, wards and other postoperative care units can change. Barz and Rajaram (2015) consider the patient-mix, having elective and non-elective patients that consume different types and quantities of resources. To maximize the total profit, the authors modelled the elective patient admission in a Markov Decision Process, using Approximate Dynamic Programming to derive upper bounds. Finally, testing different heuristics, the authors conclude that a newsvendor heuristic outperforms all other solution approaches.

3.5.2 Horizontal and Vertical Integration

The importance of accounting for stakeholders in the planning and scheduling of the OT and their integration is important for a cohesive process. Managing different services and resources separately can result in sub-optimal results, from an optimization point of view, but also increase problems related, for example, with lack of inter-department communication. In this section, we distinguish between horizontal and vertical integration. On the one hand, the horizontal integration includes the number of specialities incorporated, the number of ORs and the presence of staff rostering. On the other hand, the vertical integration includes the combination of ORs with other hospital facilities, such as preoperative holding units (PHU), PACUs, wards – that include both wards and general-purpose recovery beds – and ICUs. While the vertical integration, when present, is normally explicit in the papers, accessing the horizontal integration in each paper is harder since a vast extent of authors does not make any mention to this subject, being uncertain the plurality of ORs and specialities addressed. For this reason, Table C1 has information only on the vertical integration of each paper.

Through the performed analysis, it is possible to access that most of the papers handle multi-OR problems, although some exceptions exist, mainly when tackling the allocation scheduling problem, normally in a daily basis. Khaniyev et al. (2020) focus on the assignment of a starting and finishing hours of each surgery, given their sequence in one OR. The objective is to minimize the sum of expected patient waiting times, room idle time and overtime, considering that surgery durations are uncertain and using Myopic, Expectation, and Veteran heuristics and a hybrid heuristic. Herring and Herrmann (2012) also consider a one-room model, to perform a dynamic surgery scheduling. The authors model an OR-day with primary cases to be scheduled, and primary and secondary cases from a request queue, considering stochastic demand for surgeries with the objective of minimizing the total expected cost of primary case deferral and underutilization of the OR. On the other end of OR integration, Roshanaei et al. (2017a) studies a planning and scheduling problem consisting in a network of multiple hospitals, where ORs, patients and surgeons are collaboratively taken into consideration. Patients are assigned to a hospital, from the pool of considered hospitals. Surgeons are free to move between ORs to reduce idle times but can do so only in their respective hospital to minimize the inherent travel times. The overall objective is to reduce the number of open ORs, surgeon time and overtime usage.

Staff rostering also falls into the horizontal integration criterion. Very few authors consider any type of rostering and to our knowledge, no paper has included anaesthesiologist rostering or tackled both nurse and surgeon rostering in the same paper. Van Huele and Vanhoucke (2014) deal with the integrated physician and surgery scheduling problem to create one-week schedules. Instead of accounting for surgeons' time as a scheduling constraint or considering the tuple surgeon-patient to be previously assigned, the authors focus on assigning surgeons and cases separately to each time block, creating independent schedules. The problem of nurse rostering alongside with surgical case scheduling has also been subject of concern in the literature (Bilgin et al. 2012; Xiang et al. 2015a). Bilgin et al. (2012) suggest one hyper-heuristic based on heuristic selection mechanism and the move acceptance criterion (Özcan, Bilgin, and Korkmaz 2008) to minimize the weighted number of violations of soft-constraints related to patient and nurse preferences, e.g. minimum consecutive days of work of each nurse. In the model of Xiang et al. (2015a), the nurse rostering problem is developed to level the capacity among the OT, considering the qualification, role and availability of each nurse. An ant colony optimization approach is used to solve the problem, with the objective of minimizing the total makespan of scheduled surgeries.

Relatively to vertical integration of the ORs with other facilities, in this work are considered the PHU, PACU, wards and recovery beds, and ICU. Few authors consider the patients' stay in the PHU before surgery (Ansarifar et al. 2018; Jebali et al. 2006; Niu et al. 2013; Schmid and Doerner 2014; Xiang et al.

2015a; Xiang et al. 2015b). Niu et al. (2013) considers the number of chairs in the holding area as one of the decision variables and establishes lower and upper bounds on that number, to minimize the LOS of patients in the hospital. Scheduling of the patients' path on OR, and also PHU beds is portrayed in Xiang et al. (2015b). The authors aim to minimize the makespan of surgeries considering the LOS of the patient in different, consecutive resources, PHU beds, ORs and PACU beds. The authors model the problem as a multi-resource constrained flexible job-shop and develop an ant colony algorithm. By contrast with preoperative resource analysis that is scarce in the literature, post-operative resources are accounted in some papers with many authors recognizing their importance to the underlying problem. While some authors consider the re-routing of patients in recovery units, taking advantage of available resources while the needed are occupied (Azari-Rad et al. 2014; Lee and Yih 2014), other authors consider that the OR becomes blocked and all surgeries are delayed or cancelled until downstream resources are released (Hamid, Hamid, and Nasiri 2017). Azari-Rad et al. (2014) build a simulation of the patients' path including elective and emergency demand. After the surgery, due to the unavailability of resources, the path can change, and patients have to use other resources until their needed resource is released. Results show that having additional ward beds decreases significantly the number of surgery cancellations due to bed shortage but also decreases the average bed utilization rate. M'Hallah and Al-Roomi (2014) develop a special case where the OR is blocked if no PACU bed is available and the patient stays in the OR until a PACU bed is freed. Similarly, in the work of Fei et al. (2010), the patient is allowed to start the recovering phase in the OR if no recovery bed is available. Both papers consider resource-constrained jobs on parallel machines to minimize under- and overutilization.

3.5.3 Objective Functions

When pursuing optimality, different objective functions have been employed. In the papers analysed, 14 objectives are identified. In Table C1 it is possible to see the objectives used in each paper, enumerated from 1 to 14, as seen in Table 9. While some authors apply single-objective approaches, i.e. use only one objective to evaluate feasible solutions, most of them use more than one objective, in a multi-objective approach. Multi-objective optimization generally introduces additional complexity as the concept of optimality no longer exists but rather efficient or non-dominated solutions which are the ones belonging to a Pareto frontier. Most authors develop a weighted sum approach, in which each objective has a specific weighted contribution for a single objective function. For example, Hamid et al. (2017) considers the objective of reducing the overtime and undertime in the same objective function, setting a time underutilization cost and a time overutilization cost. Changing the relative weight of each part changes the overall score of each solution that can lead to a change in the solution (see e.g. Bilgin et al. (2012); Guido and Conforti (2017); Kamran et al. (2019, 2018); Marques and Captivo (2015)). Few authors consider various objectives in a stepwise manner, introducing them gradually in the model. For example, Meskens et al. (2013) implement a multi-objective procedure to minimize the makespan, overtime and to maximize affinities within staff members. To achieve their goal, the authors first solve the model using a single-objective function, to minimize the makespan. Once the optimal value is identified, the objective function is incorporated in the model as an additional constraint to reduce the search space. The second objective is then optimized. Once the value of this objective is reached, the procedure is repeated by incorporating it as a new constraint, to finally run the model using the last objective function to maximize affinities. Particularly, it is the only paper that explicitly tries to maximize the affinity among surgeons, nurses and anaesthesiologists.

In this work, the minimization of overtime and overutilization, and the minimization of undertime and underutilization, are addressed in the same fields, due to the difficulty in recognizing which view is applied by the authors (Cardoen et al. 2010). The most addressed objectives consist of minimizing the overtime/overutilization and minimizing the waiting time. The waiting time is mostly related to patient waiting time from the registration in the waiting list until the surgery execution. Also, the waiting time of surgeons is under study in Zhang et al. (2014). The objective is to minimize the OR idle time and thus the patient waiting time and the overtime as well. The authors apply two heuristics to dynamically schedule cases, stating that results improved the OT performance in comparison to static scheduling based on empirical rules like FCFS.

Table 9 – Objective functions and no. of papers

Objective index	Objective	No. of papers
1	Minimize the makespan	14
2	Minimize the no. of open ORs	14
3	Minimize the waiting time	39
4	Minimize the no. of unscheduled patients	21
5	Minimize the tardiness of patients	13
6	Maximize the OR utilization	19
7	Level post-operative resources	8
8	Minimize overtime/overutilization	40
9	Minimize undertime/underutilization	9
10	Minimize the no. of surgery cancellations	5
11	Maximize profits	6
12	Minimize idle time	16
13	Maximize patient preferences	9
14	Maximize staff affinity	1

Most of the objectives are related to maximizing the efficiency in OR utilization and minimizing overall operation costs, although some papers address different objectives. For example, Marcon and Dexter (2006) focus on levelling the postoperative resource utilization, by using sequencing rules to prevent peaks on demand. According to the authors, rules as longest cases first and half increase – half decrease are the rules that create more unbalancing in downstream resources, achieving very good results with half decrease – half increase and shortest cases first.

Particular models with the objective of minimizing preference violations, such as schedule children as early in the morning as possible also exist in the literature (Cardoen et al. 2009a, 2009b; Riise and Burke 2011). Cardoen et al. (2009a) and Cardoen et al. (2009b), besides scheduling children for early in the morning, also take into consideration the distance between the residential area of patients and the hospital, with the objective of scheduling patients that are further away later in the day and therefore decrease the probability of delays or no-shows.

3.6 Chapter Conclusions

In this chapter, 118 manuscripts on the operational decision level of OR planning and scheduling, from 2005 to the present are reviewed according to four domains – decision level, patient characteristics, scheduling strategies and problem features, such as uncertainty, horizontal integration and objective functions. In addition to the reviewed domains, a table summarizing all the information is showed in Appendix C (Table C1). This table summarizes the literature and helps the reader to see what is addressed in each paper, identifying papers' characteristics in a schematic way according to the framework followed and to understand the current state of the art.

Most of the present literature tackle the planning and scheduling of elective patients using block or open scheduling strategies, while the modified block strategy, although identified as more efficient, is still underlooked by most authors. Apart from elective patients, non-elective planning has been addressed more frequently over the years. The integration of uncertainty in emergency arrival has seen some rising concern in the last years, with 12 papers addressing the subject between 2015 and 2020 and 7 between 2006 and 2014. Besides uncertainty in emergency arrival, other types of uncertainty have been studied. Uncertainty on the length of stay should also be explored in more detail in facilities with low availability of downstream resources since better management of those is essential to bottleneck reductions. Very few authors consider uncertainty in the arrival of scheduled patients due to cancellations or no-shows that lead to large idle times and possible undertime, and renewable and non-renewable resource uncertainty, that may exist in hospital operations.

Although each paper brings novel perspectives, instances, models, solution approaches, and others, to our knowledge, few studies have been implemented in real scenarios. Furthermore, no study has been performed in evaluating and comparing different existing models, with the same instances. As the number of manuscripts on the OR planning and scheduling continues to rise, a benchmark with existing models, and instances from real hospitals alongside with objectives compliant with hospital stakeholders' goals should be studied.

4 Selection and Adaptation of the Models

To perform the proposed benchmark of models, assessing and comparing their solutions, the models themselves must be chosen according to objective criteria. This Chapter presents the criteria used for the selection of the manuscripts and the selected models (Section 4.1). Each model is further introduced and detailed in Sections 4.2 to 4.4. Lastly, a preliminary model comparison to understand the main similarities and differences *a priori* is performed in Section 4.5.

4.1 Criteria for Model Selection

The selection of the OR management models, as mentioned in the methodology proposition, is a major concern to hospital and particularly OR managers. To select the papers and therefore the models to participate in the proposed benchmark, multiple criteria have been developed, according to the characteristics of the case studies. Selecting models that are suited to the characteristics of the case studies allow not only for a better integration between the collected data and the models themselves but also to more realistic results, compliant with the regulations and requirements of the hospitals under study. Furthermore, if the models selected are not suited for the hospitals' reality, despite the optimality of the results, hospital and OR managers could argue about the assumptions, therefore reducing the possibility of acceptance of the conclusions of this work.

Taking into consideration all 118 manuscripts presented in the literature review, screening criteria are developed to exclude all models that are out of scope due to the following reasons:

- Since the objective is to study only the advance scheduling problem, papers that address only the allocation scheduling problem are excluded. Papers that address both the advance and the allocation scheduling problems but in an inextricable way, are excluded as well.
- In the same line as the previous criterion, papers that, although addressing advance scheduling, address both tactical and operational phases in an inextricable way are excluded.
- The hospitals under study only use block scheduling strategy, thus, papers that employ open block scheduling are excluded.
- Papers that only study the scheduling or management of urgent or emergent patients, not tackling elective patients, as required, are excluded.
- Both COTs studied in this work have multiple ORs, serving multiple specialities. For that reason, both papers that address only one-OR or one-speciality are excluded.
- Due to the necessity of implementation of the model, to perform the benchmark, papers without an explicit mathematical model formulation need to be excluded.
- Finally, only papers from 2010 to 2020 are considered, excluding non-published papers and thesis.

As can be seen in the following table (Table 10), from the 118 papers, only 12 are compliant with the stated criteria. The table also presents the uncertainty referred in each paper, namely surgery duration uncertainty and length of stay uncertainty, shown as duration and LOS. Moreover, to select among these the models to take part in the benchmark, and in line with one of this thesis' cornerstone – the stakeholder's satisfaction –, the approach of each paper towards different stakeholders was analysed. To assess the consideration for stakeholders on each paper, it was necessary to establish a correlation between those and the models' parameters and objectives. Regarding the focus on the patient, it was examined if the patient priority is taken into account in the model and if the reduction of patient waiting time (WT) is present on the models' objectives. The focus on management concerns the objective of maximizing OR utilization, minimizing overutilization and minimizing underutilization, thus reducing operating costs in the OT, which is essential for hospital and OR managers. Finally, the focus on the surgeons is more subjective, as each paper that does so considers a different approach. For example, Kamran et al. (2018, 2019) focus on surgeon's satisfaction by also minimizing the number of days each surgeon needs to perform surgery, therefore reducing the number of days required to be present in the hospital.

Table 10 – Papers compliant with the screening criteria

Autor	Uncertainty		Considerations on stakeholders			
	Duration	LOS	Focus on patient		Focus on management	Focus on surgeon
			Priority	WT		
Aringhieri et al. (2015a)			✓			
Jebali and Diabat (2015)	✓	✓			✓	
Kamran et al. (2019)	✓		✓	✓	✓	✓
Kamran et al. (2018)	✓	✓	✓	✓	✓	✓
Landa et al. (2016)	✓				✓	
Marques and Captivo (2017)	✓		✓	✓	✓	✓
Min and Yih (2010b)	✓	✓	✓	✓	✓	
Moosavi and Ebrahimnejad (2020)	✓	✓	✓	✓	✓	✓
Rachuba and Werners (2017)	✓			✓	✓	
Roshanaei et al. (2017a)			✓	✓	✓	✓
Shylo et al. (2013)	✓				✓	
Silva et al. (2015)	✓				✓	

As all selected papers are suited for the benchmark according to the screening criteria, to select the papers partaking in the benchmark, evaluation criteria must be employed. In this work, as the objective is not only to improve surgical production but also to improve stakeholders' satisfaction, only the papers that address all four stakeholder's considerations studied, shall be eligible for the benchmark. From Table 10 it is possible to see that only five papers (highlighted in the table) tackle all four stakeholder's considerations (Kamran et al. 2019, 2018; Marques and Captivo 2017; Moosavi and Ebrahimnejad 2020; Roshanaei et al. 2017a). The model presented in Roshanaei et al. (2017a) is not implemented and tested for the benchmark, since it is focused on the process of scheduling patients across multiple hospitals. Additionally, it is important to note that both Kamran et al. (2019) and Kamran et al. (2018) consider almost the same advance scheduling problem and use the same model. However, while Kamran et al. (2018) focuses only in the advance scheduling problem introducing both duration and LOS uncertainty, Kamran et al. (2019) enhances the previous model by studying both advance and allocation scheduling phases. Since in this work only the advance scheduling phase is being analysed, only the model of Kamran et al. (2018) is selected. Therefore, the selected models for the benchmark are Kamran et al. (2018), Marques and Captivo (2017), and Moosavi and Ebrahimnejad (2020). The following four subsections present in detail the models proposed in each of these three papers, respectively, plus a preliminary comparison between them. Being the objective of this work to perform a comparative study of the models and their solutions, only an introduction and the model formulation alongside with insight on the objective functions and constraints are presented. More detail can still be found in the respective manuscripts – Kamran et al. (2018), Section 4.2, Marques and Captivo (2017), Section 4.3, and Moosavi and Ebrahimnejad (2020), Section 4.4.

4.2 Kamran et al. (2018)

In the manuscript, Kamran et al. (2018) consider a multi-objective advance scheduling problem to schedule elective and non-elective patients in a modified block scheduling strategy. The authors formulate a mixed integer linear programming model, based on Addis et al. (2014), to select candidate patients from the patients' waiting list and allocate them a date and a proper OR block. Additionally, the model is used to determine the amount of overtime per block and determine if the surgeon is scheduled for surgery in a given day. To deal with non-elective patients, authors use slack time, by defining an occupation parameter of each individual block, leaving free time for emergency cases. In the present work, under the assumption that the studied blocks in the ORs are used only for elective cases and the number of non-elective patients is zero, the occupation parameter is set to 1. It is important to refer that the model includes different patient priorities, established a priori. The MSS and the surgeon assigned to each patient have also to be known beforehand. The length of the MSS, equivalent to the planning horizon in the model, can be set as multi-week, defining the number of weeks with the parameter w. However, since the MSS of both CHLN and HESE have the length of one week, this parameter is considered as 1. The formulation of the deterministic model is presented below.

<u>Sets and Parameters</u>

p	index for elective patients (p = 1, …, P, where P is the number of elective patients)
r	index for operating rooms (r = 1, …, R , where R is the number of operating rooms)
b	index for blocks (b = 1, …, B, where B is the total number of blocks in all ORs)
s	index for surgeons (s = 1, …, S, where S is the number of surgeons)
e	index for expertise (specialities) (e = 1, …, E, where E is the number of specialities)
d	index for days (d = 1, …, D, where D is the number of days in the planning horizon)
w	index for weeks (w = 1, …, W, where W is the number of weeks)
C_{bdw}	capacity of block b in day d in week w
γ_{bdw}	occupation parameter of block b in day d in week w
$\bar{t}_p$	expected surgery duration of patient p
A_p	release time/date for the surgery of patient p
D_p	due time/date for the surgery of patient p

U_p clinical priority coefficient of patient p

m_j weight of term j (j = 1, …,7) in the objective function

B^E_{edw} set of blocks which are assigned to expertise e in day d in week w

E^P_p expertise which patient p needs (E^P_p = 1, …, E)

B^R_{rdw} set of blocks which are assigned to room r in day d in week w

S^P_p surgeon who should/will operate patient p (S^P_p = 1, …, S)

O^{max}_b maximum overtime allowed by each block b

O^{max}_r maximum overtime allowed by each operating room r

N^{max}_s maximum number of surgeries allowed to be accomplished in a day by a surgeon

D_{dw} total number of waiting days by a patient during the planning horizon

Decision variables

x_{pbdw} 1, if patient p is scheduled to be operated in block b in day d in week w; 0 otherwise

o_{bdw} amount of overtime of block b in day d in week w

n_{sdw} 1, if surgeon s is scheduled for surgery in day d in week w; 0 otherwise

Deterministic model formulation

$$\min \ (\sum_p \sum_b \sum_d \sum_w [\, m_1 \left(D_{dw} - A_p \right) + m_2 \left(D_{dw} - D_p \right)^+] * x_{pbdw} * U_p \,)$$
$$+ (\sum_{p:\, D_p \leq D*W} [\, m_3 \left(D_p - A_p \right) + m_4 \left(D * W - D_p \right)] * (1 - \sum_b \sum_d \sum_w x_{pbdw} \,) * U_p \,) \tag{A.1}$$
$$+ \ m_5 \,(\, P - \sum_p \sum_b \sum_d \sum_w x_{pbdw} \,) + \ m_6 \,(\sum_s \sum_d \sum_w n_{sdw} \,) + \ m_7 \,(\sum_b \sum_d \sum_w o_{bdw} \,)$$

Subject to:

$$\sum_w \sum_d \sum_{b \in [\, B^E_{ed} \,|\, E^P_p = e \,]} x_{pbdw} \leq 1 \qquad \forall p \tag{A.2}$$

$$\sum_p \bar{t}_p * x_{pbdw} \leq (\gamma_{bdw} * C_{bdw}) + o_{bdw} \qquad \forall b, d, w \tag{A.3}$$

$$o_{bdw} \leq O^{max}_b \qquad \forall b, d, w \tag{A.4}$$

$$\sum_p \sum_{b \,\in\, B^R_{rdw}} \bar{t}_p * x_{pbdw} \leq \sum_{b \,\in\, B^R_{rdw}} [\, (\gamma_{bdw} * C_{bdw}) + o_{bdw} \,] \qquad \forall r, d, w \tag{A.5}$$

$$\sum_{b \,\in\, B^R_{rdw}} o_{bdw} \leq O^{max}_r \qquad \forall r, d, w \tag{A.6}$$

$$D_{dw} \geq A_p * \sum_b x_{pbdw} \qquad \forall p, d. w \tag{A.7}$$

$$\sum_b x_{pbdw} \leq n_{sdw} \qquad \forall p{:}\, S^P_p = s, \forall s, d, w \tag{A.8}$$

$$\sum_{p:\, S^P_p = s} \sum_b x_{pbdw} \leq N^{max}_s \qquad \forall s, d, w \tag{A.9}$$

$$x_{pbdw} \ \in \{0, 1\} \qquad \forall p, b, d, w \tag{A.10}$$

$$n_{sdw} : integer \qquad \forall s, d, w \tag{A.11}$$

$$o_{bdw} \geq 0 \qquad \forall b, d, w \tag{A.12}$$

In the stated model, objective function (A.1) is comprised of seven terms, each with an established weight, $m_j,\ j = 1, \dots 7$. The first term is the penalty for the weighted sum of waiting time whereas the second term is the weighted sum for tardiness, both for scheduled patients. In the second term $\left(D_{dw} - D_p\right)^+ = \max\{D_{dw} - D_p, 0\}$. The third and fourth terms are analogous to the first two, but for the unscheduled patients whose due times are within the planning horizon. All these mentioned terms have in consideration the patient priority U_p, to give preference to patients with higher priorities. The fifth term, which comprises the total number of patients to schedule P minus the number of scheduled patients, is the penalty for the number of unscheduled patients. The sixth term penalizes the total number of working days surgeons are required to perform surgeries. Finally, the seventh term minimizes the sum of overtime in the blocks for the planning horizon.

Constraints (A.2) guarantees that each patient can be scheduled at most once. Constraints (A.3) calculate the overtime in each block of the planning horizon and Constraints (A.4) force it to be no more than the maximum block overtime O_b^{max} in each block. Analogously, Constraints (A.5) compute the overtime per room and Constraints (A.6) force it to be no more than the maximum room overtime O_r^{max}. Constraints (A.7) enforce that surgeries can only be scheduled after the release time of each surgery (A_p). Constraints (A.8) ensures n_{sd} to be 1 for each block a surgeon has surgeries scheduled in a given day. Constraints (A.9) guarantee that each surgeon performs no more than the maximum permitted number of surgeries in each day. Finally, Constraints (A.10)–(A.12) indicate the domain of variables.

4.3 Marques and Captivo (2017)

The model presented by Marques and Captivo (2017) is a multi-objective, mixed integer linear programming model. Having the stakeholders in the centre of their approach, the authors consider three different models, by adapting mainly the objective functions to the stakeholder's needs, leading to the formulation of the administration's point-of-view model, the surgeon's point-of-view model and a mix of both, trying to achieve the best trade-off between the two stakeholders. In the administration's version, the objectives are set as the desired scenario pursued by the SNS and, therefore, the hospital's administration. The aim is to improve equity in the access, timely access and the use of the OR available time. The surgeons' version, in turn, represents the current practice at the hospital, applying different objectives for the morning and the afternoon shift. In the morning shift the authors consider a last-in-first-out strategy, mimicking the surgeon's "lack of memory", implying that surgeons prefer to operate patients who remember best. For the afternoon shifts, due to extra-contractual incentives of the hospital, the objective is extended to include a maximization on the number of surgeries. In the mixed version, the authors consider the morning shift to be equal to the administration's version and the afternoon shift to be equal to the surgeon's version, keeping the incentive programme. Both the surgeon's and the mixed versions follow a two-stage optimization approach, scheduling first for the morning shift and later, in the second stage, surgeries not scheduled in the first one are scheduled in the afternoon. The administration's model is presented below, followed by the surgeons' model.

Sets and Parameters

c	index for elective surgeries (c = 1, …, C, where C is the number of elective surgeries)
s	index for surgical services (s = 1, …, S , where S is the number of surgical services)
h	index for surgeons (h = 1, …, H, where H is the number of surgeons)
d	index for days (d = 1, …, D, where D is the number of days in the planning horizon)
b	index for time blocks (b = 1, …, B_d, where B_d is the number of time blocks available in day d)
j	shifts (j = M, A : M = Morning and A = Afternoon)
dd_c	due date for surgery c
C_{bd}	capacity of block b in day d
d_1	first planning day
wl_c	number of days that surgery c is in the waiting list at the first planning day
s_c	surgical service of surgery c
h_c	surgeon responsible for surgery c
w_c	penalty for not scheduling surgery c, $\forall c \in C^{NP}$
p_c	Priority level of surgery c (1 = normal, 2 = priority, 3 = high priority, 4 = deferred urgency)
t_c^{TOT}	room occupation for surgery c (in minutes)
t_c^{SRG}	surgeon occupation for surgery c (in minutes)
t_c^{CLN}	cleaning time for surgery c (in minutes)
a_{db}^s	1 if block b on day d is assigned to surgical service s; 0, otherwise
k_{db}^B	capacity of block b on day d (in minutes)
k_{hd}^H	capacity of surgeon h to operate on day d (in minutes)
k_h^H	capacity of surgeon h to operate during the planning horizon (in minutes)
C_d^P	deferred urgency surgeries with due date on day d in the planning horizon: $C_d^P = \{ c \in C: dd_c = d, p_c = 4 \}, d \in D$
C^{NP}	surgeries with due date out of the planning horizon or non-deferred urgency surgeries: $C^{NP} = \{ c \in C: dd_c \notin D, p_c \neq 4 \}$
D_c	days available for scheduling surgery c: $D_c = \begin{cases} \{ d \in D: d \leq dd_c \}, & c \in C_d^P, d \in D \\ D, & c \in C^{NP} \end{cases}$
C_{db}	surgeries that can be scheduled in time block b of day d: $C_{db} = \{ c \in C: a_{db}^s = 1, s_c = s, d \in D_c\}$
C_h^H	surgeries with responsible surgeon h : $C_h^H = \{ c \in C: h_c = h \}$
C_{hd}^H	surgeries with responsible surgeon h that can be scheduled in day d : $C_{hd}^H = \{ c \in C: h_c = h, d \in D_c \}$
C_s^S	surgeries belonging to service s : $C_s^S = \{ c \in C: s_c = s \}$
C_{sh}^S	surgeries belonging to service s that can be scheduled in day d : $C_{sh}^S = \{ c \in C_h^H: s_c = s \}$
B_d^j	time blocks available in shift j in day d
B_{dc}	time blocks available in day d for scheduling surgery c : $B_{dc} = \{ b \in B_d: a_{db}^s = 1, s_c = s \}$
B_{dc}^j	time blocks available in shift j in day d for scheduling surgery c

Decision and auxiliary variables

x_{cdb} 1, if surgery c is scheduled to block b in day d; 0 otherwise ($c \in C;\ d \in D_c;\ b \in B_{dc}$)

z_c 1, if surgery c is not scheduled; 0 otherwise ($c \in C^{NP}$)

Deterministic model formulation (Administration version)

$$\min \left(\sum_{c \in C} \sum_{d \in D_c} \sum_{b \in B_{dc}} [(dd_c - d_1) + d] * x_{cdb}\right) + \sum_{c \in C^{NP}} p_c * w_c * z_c \tag{B.1}$$

Subject to:

$$\sum_{d' \leq d} \sum_{b \in B_{d'c}} x_{cd'b} = 1 \qquad \forall c \in C_d^P, d \in D \tag{B.2}$$

$$\sum_{d \in D} \sum_{b \in B_{dc}} x_{cdb} + z_c = 1 \qquad \forall c \in C^{NP} \tag{B.3}$$

$$\sum_{c \in C_{db}} (t_c^{TOT} + t_c^{CLN}) * x_{cdb} \leq k_{db}^B \qquad \forall d \in D, b \in B_d \tag{B.4}$$

$$\sum_{c \in C_{hd}^H} \sum_{b \in B_{dc}} t_c^{SRG} * x_{cdb} \leq k_{hd}^H \qquad \forall h \in H, d \in D \tag{B.5}$$

$$\sum_{c \in C_h^H} \sum_{d \in D_c} \sum_{b \in B_{dc}} t_c^{SRG} * x_{cdb} \leq k_h^H \qquad \forall h \in H \tag{B.6}$$

$$\sum_{c \in C_{hd}^H} \sum_{b \in B_{dc}^j} t_c^{SRG} * x_{cdb} \leq \max_{b \in B_d^j} k_{db}^B \qquad \forall h \in H, d \in D, j = \{M, A\} \tag{B.7}$$

$$x_{cdb} \in \{0, 1\} \qquad \forall c \in C, d \in D_c, b \in B_{dc} \tag{B.8}$$

$$z_c \geq 0 \qquad \forall c \in C^{NP} \tag{B.9}$$

In the manuscript, the authors state that the objective function aims to improve equity in the access, timely access and also the use of the OR available time. Objective Function (B.1), comprises two terms. In the first term, patients are scheduled through the minimization of the number of days until due date/TMRG from the first day in the planning horizon ($dd_c - d_1$), which implies a FIFO strategy for patients with the same TMRG. To force the surgeries to be scheduled as early as possible in the planning horizon, index d is used. Note that for episodes that already passed the due date, the first term of (B.1) is negative. The second term of the Objective function (B.1) is employed to penalize surgeries not scheduled. This penalization forces the model to schedule surgeries in function of the priority level p_c and waiting cost w_c (penalty for not scheduling the surgery). This penalty depends on the number of days until due date, with $w_c = (dd_c - d_1) * 1{,}2 + P$. The factor P is a step function defined in the model's parameters (Section 5.2). The contribution of Objective function (B.1) is thus twofold, contributing for scheduling surgeries (first term) and an alternatively, contributing if the same surgery is not scheduled (second term).

Constraints (B.2) ensure that all deferred urgency surgeries are scheduled once in the planning horizon, within their due date (in a day d' at the latest equal to due date d). Constraints (B.3) regards all surgeries with due date out of the planning horizon or non-deferred urgencies. Such surgeries can only be scheduled (x_{cdb}) or not scheduled (z_c) once in the planning horizon. The time block capacity is featured in Constraints (B.4) which ensures that the sum of the total time that a patient is in the room (t_c^{TOT}) and the cleaning time needed after the patient leaves the room (t_c^{CLN}) is no more than the block capacity. Constraints (B.5) force the daily operating time for each surgeon to be no more than the maximum allowed for the day, whereas Constraints (B.6) force the weekly operating time of each surgeon to be no more than the maximum allowed for the week. To ensure non-overlapping of surgeons amongst ORs during the same shift, Constraints (B.7) is necessary, as they limit the sum of operating time of surgeons t_c^{SRG} in each shift to the longest time block duration in the shift ($\max k_{db}^{B}$). Although the ordering of surgeries in the allocation scheduling can still influence overlapping, when no sequence exists, Constraints (B.7) are sufficient. It is important to note that it is redundant if $k_{hd}^{H} \leq \max_{b \in B_d^j} k_{db}^{H}$ $, j = M, A$. Finally, constraints (B.8) and (B.9) indicate the domain of variables.

<u>Deterministic model formulation (Surgeons' version)</u>

The surgeons' version of the model comprises two objective functions, one for the morning shifts and another for the afternoon shifts, presented below.

<u>Morning Shifts</u> ($j = M$):

$$\min \left(\sum_{c \in C} \sum_{d \in D_c} \sum_{b \in B_{dc}} (wl_c + d) * x_{cdb} + \sum_{c \in C^{NP}} (2 * \max_{c \in C}(wl_c) - wl_c + (|D| + 2)) * z_c\right) \tag{B.10}$$

Subject to:

(B.2) – (B.9) with $j = M$ in constraints (B.7)

<u>Afternoon Shifts</u> ($j = A$):

$$\max \left(\sum_{c \in C} \sum_{d \in D_c} \sum_{b \in B_{dc}} \left(1 - \frac{wl_c}{1 + \max_{c \in C}(wl_c)}\right) * x_{cdb}\right) \tag{B.11}$$

Subject to:

(B.2), (B.4), (B.7) with $j = A$, (B.8)

$$\sum_{d \in D_c} \sum_{b \in B_{dc}} x_{cdb} \leq 1 \qquad \forall c \in C^{NP} \tag{B.12}$$

Objective function (B.10) has also two terms and aims to minimize the waiting time for the scheduled surgeries. The first term penalizes episodes with higher wating times, which is thought to reflect the hospital's current practice, where surgeons schedule patients that they remember best. Thus, patients are scheduled in the inverse order as they arrive in the waiting list (LIFO strategy). Like Objective function (B.1), index d is used to force surgeries to be scheduled as early as possible in the planning horizon. The second term models the penalization for not scheduling the surgeries, forcing surgeries to be scheduled. Similarly to the first term, this penalization term negatively depends on the number of days in the waiting list at the first day of the planning horizon. In the stated term, the coefficients for not scheduling the surgeries are higher than the coefficients for scheduling the corresponding surgery ($2 * \max_{c \in C}(wl_c) - wl_c + (|D| + 2) > wl_c + d, \quad \forall c \in C^{NP}, d \in D$) thus forcing the surgeries to be scheduled in the planning horizon.

For the afternoon shift, Objective function (B.11) aims at maximizing the use of the surgical resources available and the access and thus the maximization of the number of surgeries scheduled is considered.

Since the surgeons' "lack of memory" (scheduling cases with lower waiting times) is present both in morning and afternoon shifts, a LIFO strategy is also followed when scheduling patients in the afternoon shifts. To this end, a perturbation factor is minimized. This perturbation factor is a function of the percentage of days that surgery c is in waiting list (wl_c) in relation to the maximum number of days waiting over all the surgeries in the list ($1 + \max_{c \in C}(wl_c)$) ; one unit is added in order to avoid coefficients equal to zero for the patients that have the maximum waiting time). Since auxiliary variables z_c are not needed to formulate objective function (B.11) of the afternoon shifts stage, Constraints (B.3) are replaced by Constraints (B.12).

A third version is also formulated in Marques and Captivo (2017), mixing the above two. In this mixed version, halfway between the surgeons' model and the administration's model, the morning shifts are scheduled in accordance with the administration's version – minimization of (B.1), s.t.: (B.2) – (B.9), with $j = M$ in constraints (B.7) – and the afternoon shifts are scheduled in accordance with the surgeons' version – maximization of (B.11), s.t.: (B.2), (B.4) – (B.7) with $j = A$, (B.8), (B.12).

In the following chapters, all three versions of the model are implemented, and the solutions compared.

4.4 Moosavi and Ebrahimnejad (2020)

In the work of Moosavi and Ebrahimnejad (2020), the authors tackle the OR planning problem at both tactical and operational levels. The mathematical model consists in a multi-objective mixed integer linear programming model with the primary objective of scheduling patients in different ORs over the planning horizon. The model considers the scheduling of elective and non-elective patients by setting a number of dedicated time slots for the later. In the current dissertation, as only the scheduling of elective patients is contemplated, the number of dedicated time slots for non-elective patients is considered zero. More detail on the specific parameters used to validate the models and perform the benchmark are presented in Section 5.2. As it is focused on the tactical level as well, besides assessing the undertime and overtime of each OR, the model developed in Moosavi and Ebrahimnejad (2020) has also the objective of assessing which ORs to open or close during the planning horizon to reduce costs and assign them a speciality. In this work, having an MSS beforehand, the assignment of specialities to ORs and which ORs to open or close is given as a model's parameter and not a model's decision. Another particular feature of this model, although not present on the formulation below and not having been implemented in this work for being out of scope, is the addition of resources such as ICU beds and ward beds. An objective to level the upstream and downstream units is set, minimizing the deviation from the average number of beds used in both, while ensuring that every scheduled patient has access to a bed when needed. The model is presented below.

<u>Sets and Parameters</u>

I	Surgical cases	$I = \{1,2,\cdots,I\}$
IF	Surgical cases for whom performing surgery is obligatory within the planning horizon	$IF = \{1,2,\cdots,IS\}$
IO	Surgical cases that could be either operated within the planning horizon or deferred to the next planning horizons	$IO = \{IS+1, IS+2,\cdots,I\}$

S	Specialties	$S = \{1,2,\cdots,J\}$
SF	Specialties that can only operate in certain ORs	
SO	Specialties that can operate in all ORs	
$\mathcal{K}$	Surgery types	$\mathcal{K}$={1,2,⋯,K}
R	ORs	$\mathcal{R}$={1,2,⋯,R}
$R\mathcal{F}_j$	ORs where specialty j can operate in	
$\mathcal{T}$	The planning horizon	$\mathcal{T} = \{1,2,\cdots,T,T+1\}$
$\mathcal{T}P$	Days of the planning horizon in which surgical cases can be operated	$\mathcal{T}P = \{1,2,\cdots,T\}$
P_{1jk}	The surgery duration for a surgical case of specialty j and type k	
P_{2jk}	The sterilization time for a surgical case of specialty j and type k	
SL	The regular time that ORs are open before the start of overtime	
TO	The time that ORs could be kept open after SL time slots	
ST_j	Number of surgery teams available for specialty j at each day	
MB_j	The utmost number of OR-days in which specialty j can operate	
M_1	Adequately large coefficient	
E_t	The estimate of emergency demands on day t	
NMX	The utmost number of ORs which could accommodate emergency demands within a day	
ID_{ijk}	1, if surgical case i relates to specialty j and requires surgery of type k; 0, otherwise	
WT_i	WT of surgical case i at the start of the planning horizon (measured in days)	
L_{jk}	Number of days that a surgical case of specialty j and type k can wait on the waiting list without incurring in Waiting Cost	
WC_{jk}	Waiting Cost for a surgical case of specialty j and type k	

Decision variables

o_{rt}, u_{rt}	Overtime and idleness in OR r on day t, respectively
x_{irt}	1, if surgical case i is allocated to OR r on day t; 0, otherwise
z_{jrt}	1, if specialty j is allotted to OR r on day t; 0, otherwise
y_r	1, if OR r is opened throughout the planning horizon; 0, otherwise
n_{rt}	1, if OR r accommodates emergency demands on day t; 0, otherwise

Deterministic model formulation

$$\text{Min } f_1 = \sum_{i\in I}\sum_{j\in S}\sum_{k\in\mathcal{K}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} \left[\left(WT_i + t - L_{jk}\right)^+\right]^2 \cdot ID_{ijk} \cdot WC_{jk} \cdot x_{irt} \tag{C.1}$$

$$\text{Min } f_2 = \sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}P} (o_{rt} + u_{rt}) - |TP| \cdot SL \cdot \sum_{r\in\mathcal{R}} (1 - y_r) \tag{C.2}$$

Subject to:

$$x_{irt} \le z_{jrt} \qquad \forall i \in I; j \in \mathcal{S}; r \in \mathcal{R}; t \in \mathcal{TP}; \sum_{k\in\mathcal{K}} ID_{ijk} = 1 \tag{C.3}$$

$$\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} x_{irt} = 1 \qquad \forall i \in IO \tag{C.4}$$

$$\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{TP}} x_{irt} = 1 \qquad \forall i \in I\mathcal{F} \tag{C.5}$$

$$\sum_{r\in\mathcal{R}} em_{rt} - E_t = 0 \qquad \forall t \in \mathcal{TP} \tag{C.6}$$

$$em_{rt} \leq n_{rt} \cdot M_1 \qquad \forall r \in \mathcal{R}; t \in \mathcal{TP} \tag{C.7}$$

$$em_{rt} \geq n_{rt} \qquad \forall r \in \mathcal{R}; t \in \mathcal{TP} \tag{C.8}$$

$$n_{rt} \leq y_r \qquad \forall r \in \mathcal{R}; t \in \mathcal{TP} \tag{C.9}$$

$$\sum_{r\in\mathcal{R}} n_{rt} \leq NMX \qquad \forall t \in \mathcal{TP} \tag{C.10}$$

$$\sum_{i\in I}\sum_{j\in S}\sum_{k\in\mathcal{K}} \left(\left(P_{1jk} + P_{2jk}\right) \cdot ID_{ijk} \cdot x_{irt}\right) + em_{rt} + u_{rt} = SL + o_{rt} \qquad \forall r \in \mathcal{R}; t \in \mathcal{TP} \tag{C.11}$$

$$o_{rt} \leq TO \qquad \forall r \in \mathcal{R}; t \in \mathcal{TP} \tag{C.12}$$

The model presented comprises Objective functions (C.1) and (C.2). The first Objective function (C.1) minimizes surgical cases' waiting cost, reducing the waiting cost of scheduled and non-scheduled episodes. Similarly to the notation in the model of Kamran et al. (2018), $\left(WT_i + t - L_{jk}\right)^+ = \max\{WT_i + t - L_{jk}, 0\}$. Hence, no negative term is achievable, and the power of two is only used to increase the difference between solutions non-linearly. Also, it is important to note that all episodes out of due date, have zero score in this first function, creating no distinction between the episodes with different number of days out of due date. With the use of index t, the model forces surgeries to be scheduled as early as possible in the planning horizon. The second Objective function (C.2) is composed by two terms. The first aims at reducing the total overtime and undertime in ORs. As can be seen, the overtime and idleness are weighted equally in the paper. The second term of Objective function (C.2) reduces the number of opened ORs in the planning horizon. Constraints (C.3) guarantee that each surgery can only be assigned to an OR-day if the same surgery's specialty has been allotted to the same OR-day. As the planning horizon in this model incorporates an additional day to include all non-scheduled surgeries, Constraints (C.4) make sure that all surgeries can either be operated within the planning horizon $\mathcal{T}$. To complement the previous, Constraints (C.5) ensure that surgeries which are required to be performed must be operated within the planning horizon $\mathcal{TP}$ (since $\mathcal{TP} = \mathcal{T} \setminus \{T+1\}$). Constraints (C.6) specify that on each day, the time allocated to emergency surgeries in all ORs must be equal to the predicted emergency demand. Although implemented to easily change the emergency demand for future scenarios, as in the other models, the emergency demand in the planning horizon is disregarded and considered zero in this dissertation (see Section 5.2). Constraints (C.7) and (C.8) determine which ORs serve emergency demands on day t. In Constraints (C.7), M_1 refers to an adequately large coefficient. Since the sum of em_{rt} for a given day is no more than the maximum emergency demand in each day, i.e., $\max_t E_t$, the authors established M_1 equal to $\max_t E_t$. Constraints (C.8) determine that in rooms that serve emergencies, at least one time-block must be used for those surgeries. Constraints (C.9) ensure that only open rooms can accommodate emergency demands. By imposition of the hospitals, a parameter NMX to set the utmost number of ORs that can accommodate emergency surgeries in each day is envisioned. This parameter is used in Constraints (C.10) to ensure that the number of ORs accommodating emergency demands is no more than NMX. Constraints (C.11) determine the over- and undertime in each block. The adapted model concludes with constraints (C.12) which guarantee that the overtime in each OR is no more than the maximum established TO.

4.5 Model Comparison

Even though addressing the OR scheduling problem at the operational level – advance scheduling phase –, each one of the five models encompasses different approaches, having different initial assumptions and considering unique parameters. Despite meeting all the chosen selection criteria, the model of Moosavi and Ebrahimnejad (2020) has a broader spectrum of goals and, through the adaptation performed in this work, focusing only on part of them can lead to sub-optimal results in the needed objectives, when compared with models that focus only on those objectives. As seen previously, while Kamran et al. (2018) and Marques and Captivo (2017) focus only on the operational level, Moosavi and Ebrahimnejad (2020) also covers tactical decisions. In their original model, one of the decisions is to allot specialities to ORs, based on the surgical volume of the speciality for the planning horizon, as well as the decision of opening or closing ORs. In this work, similarly to the models of Kamran et al. (2018) and Marques and Captivo (2017), the assignment of specialities to blocks is given *a priori* for all three models. Furthermore, Moosavi and Ebrahimnejad (2020) also envision, at the tactical level, the distribution of beds and a levelled used of these resources.

Regarding the considered objectives, it is interesting to analyse which mechanisms are used to schedule patients. One of the main differences concerns the variables which are studied in the functions (in these cases, the scheduled patients or the unscheduled patients). Most models have the objective of selecting patients with larger waiting times of higher priority. The administration version of Marques and Captivo (2017) considers two distinctive terms for both scheduled and unscheduled patients, removing the linearity between scheduling or not scheduling a patient. This allows to increase the relevance of patients with higher priority or smaller number of days until TMRG. In the particular case of this version of the model, there is a step-wise increasing penalty based on the TMRG for not scheduling patients, which suggests that patients with a higher number of days out of TMRG are unproportionally more plausible to be selected.

Kamran et al. (2018) and Moosavi and Ebrahimnejad (2020) consider similar cases of having an extra day in the planning horizon where all the episodes that have not been selected yet are allocated. In Moosavi and Ebrahimnejad (2020), the value of the function for the scheduling of patients varies between zero for patients out of TMRG and a positive value for each patient within TMRG. Although giving priority to episodes out of TMRG, by the minimization of the overall score, it also implies that there is no implicit order for selecting these episodes based on this parameter (as they are all zero in that objective function). The same occurs in the model of Kamran et al. (2018) during the planning horizon (zero for patients out of TMRG) although, for the patients not selected, the actual number of days until due date and priority are considered. By considering an extra penalization for unscheduled episodes, when compared to Moosavi and Ebrahimnejad (2020), the Kamran et al. (2018) model is expected to schedule more patients, thus reducing the unscheduled list. In an opposite point-of-view, the surgeon's version of Marques and Captivo (2017) benefits patients with lower waiting times. With the objective of scheduling surgeries that entered the list more recently and at the same time, considering a penalization for not scheduling surgeries, it is expected that a high number of surgeries are going to be scheduled but with the minimum waiting time possible. This particularity, even though not in accordance with the order in which patients enter the waiting list, is important to be considered as it mimics the surgeons' real behaviour at the hospitals. For that reason, Marques and Captivo (2017) developed a mixed version of the two models, being a combination of the administration version for the morning shifts and the surgeons' one in the afternoon shifts as detailed previously. The mixed version is expected to significantly improve the number of scheduled patients with higher waiting times when compared to the surgeons' version, although not reaching the volume of the administration's version for these patients. On the other hand, by having a second penalization for patients not scheduled, the number of scheduled episodes is deemed to increase in relation to the administration's model.

Besides the scheduling of patients, other objectives and restrictions are also considered in the models. Both Kamran et al. (2018) and all Marques and Captivo (2017) versions of the model bear into consideration a maximum operating capacity for the surgeons, in number of operations and minutes of operation, respectively. That parameter is not envisioned in the model of Moosavi and Ebrahimnejad (2020) but can be highly useful when implementing models in hospitals where capacity limits are imposed for the surgeons. In this dissertation, this does not affect the performance, as no limits are established (see Section 5.2) in any model. Kamran et al. (2018) extends the considerations for surgeons by including an objective to minimize the number of working days per surgeon as well. Hence, it is expected that this model has a lower average of working days per surgeon when compared to the others. Furthermore, it includes an objective on the minimization of overutilization, while Moosavi and Ebrahimnejad (2020) encompasses not only the overutilization but also the reduction of underutilization. Marques and Captivo (2017), on the contrary do not allow any overutilization in the models.

4.6 Chapter Conclusions

To choose the models to compare in the benchmark, screening and selection criteria are established. The former are utilized to exclude papers that are not suited to the case study of this work, either due to studying different problems or due to having assumptions that would conflict with the reality of CHLN and HESE. The latter are used to select the final models based on the paper's inclusion of four stakeholder considerations, namely focus on patients, through waiting times and priority, focus on management and focus on surgeons. Three papers have been selected – Kamran et al. (2018), Marques and Captivo (2017) and Moosavi and Ebrahimnejad (2020). The models of the papers to be tested in the benchmark are presented, analysed and finally compared.

To understand the impact of each term of the objective functions and restrictions of the models, and to test the models in the benchmark, it is necessary to know which parameters are to be considered in them and the instances to be tested. The next chapter introduces the data for both CHLN and HESE and the specific parameters for each model.

5 Data Collection and Parameters Specification

To complement the mathematical models already detailed in the previous Chapter 4, Section 5.1 introduces the instances from the hospitals to be used, including the waiting lists and the MSS, while Section 5.2 presents other needed parameters for the models.

5.1 Hospitals' Parameters Specification

The parameters used in this thesis are organized by their nature, namely hospital related, and model related. Hospital related parameters comprise the waiting list and the MSS while model related parameters are for example, the objective function weights, overtime settings and other parameters specific for each model. The waiting list and MSS of CHLN and HESE are detailed in Subsections 5.1.1 and 5.1.2 respectively.

5.1.1 CHLN Waiting List and MSS

To assess all parameters of the CHLN waiting list to be used, historical records of the hospital's waiting list from April 18th, 2016 were provided. The surgery time, which was lacking in the given waiting list, was calculated from the average room utilization time and surgeon utilization time, computed from the surgical activity records of 2013, 2014 and 2015, and were indexed by the diagnosis and procedure followed in each surgery. Episodes in the waiting list with the same diagnosis and procedure proposal were assigned the same average time. This assumption allowed to assign an estimate of room and surgeon utilization time for 3 033 episodes out of 3 119 – approximately 97,2% - and the remaining 86 entries were excluded for lack of data. The overall average of surgeon and room utilization time and the respective standard deviation from the analysed data are shown in Figure 4.

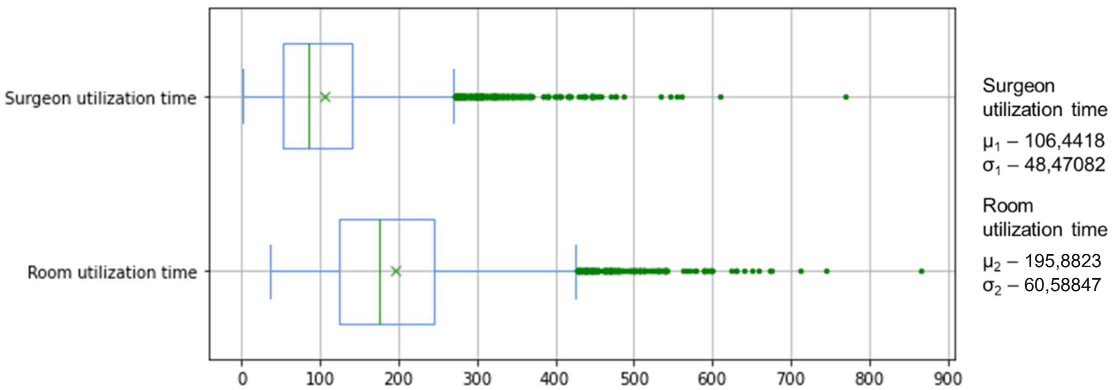

Figure 4 – Boxplots of surgeon (top) and room (bottom) utilization time for the surgical activity record of 2013 to 2015 at CHLN

The respective average surgeon and room utilization time for each speciality of the CHLN COT are presented in Table 11. The specialities under study in the case of CHLN, as mentioned in Chapter 2, are general surgery, orthopedy, urology and vascular surgery. Main figures, such as the number of surgeons for each specialty, the number of episodes, and the durations are also included in Table 11. The field due date is calculated as the number of days remaining from the beginning of the planning horizon until the actual due date to perform surgery. As can be seen, the average number of days until due date in the case of orthopedy and vascular surgery, although positive, are very low and, in fact, a large number of episodes are already out of TMRG – tardy episodes –, as is shown in Figure 5.

Table 11 – CHLN surgical specialities, speciality groups, number of surgeons and waiting list information

Speciality group	**No. of surgeons**	**No. of episodes WL**	**Avg. surgery duration (min)**	**Avg. room duration (min)**	**Avg. episode due date (days)**
General Surgery	48	526	78,4	155,9	104,9
Orthopedy	30	894	125,2	228,9	2,6
Urology	31	572	57,9	122,9	64,0
Vascular Surgery	29	1 041	79,2	150,4	5,4

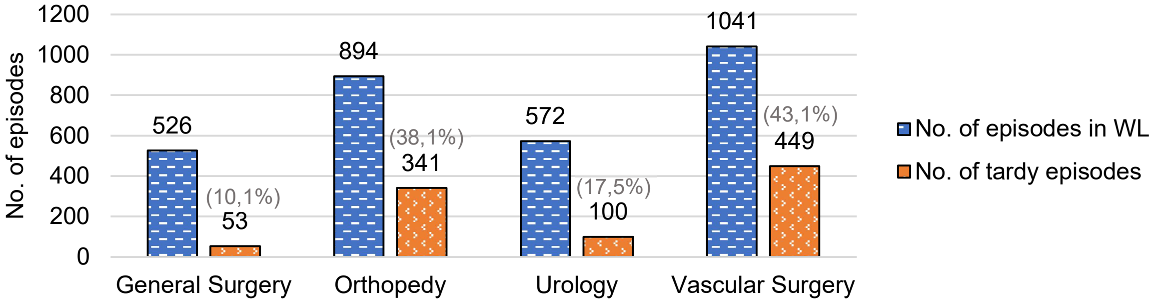

Figure 5 – No. and percentage of episodes in CHLN WL out of TMRG

Besides the waiting list, the model also uses as input a MSS. Although it is presented in Chapter 2 an up-to-date MSS for the hospital's COT, the MSS used in the models differs from this one. The MSS used in the models (Table 12) is based on the surgical activity of the COT for the week under study – 18 to 22 of April 2016 –, to replicate as much as possible the same conditions. The morning blocks have a capacity of 7 hours * 60 = 420 minutes and the afternoon blocks have a capacity of 4 hours * 60 = 240 minutes, with the exception of OR 3B on Friday, in which the morning block has a capacity of 360 minutes. Blocks with no speciality assigned have a capacity of zero minutes.

Table 12 – CHLN planned MSS and block capacity (minutes)

		Mon		**Tue**		**Wed**		**Thu**		**Fri**	
OR 1A	M	Ortho	420	Ortho	420	Ortho	420	Ortho	420	-	0
	A	-	0	-	0	Ortho	240	-	0	-	0
OR 1B	M	Ortho	420	Ortho	420	Ortho	420	Ortho	420	Ortho	420
	A	-	0	-	0	-	0	-	0	-	0
OR 2A	M	General	420	General	420	General	420	General	420	General	420
	A	General	240	General	0	-	0	-	0	-	0
OR 2B	M	General	420	General	420	General	420	General	420	General	420
	A	General	240	General	240	-	0	-	0	General	240
OR 3A	M	Vascular	420	Vascular	420	Vascular	420	Vascular	420	Vascular	420
	A	Vascular	240	Vascular	240	Vascular	240	Vascular	0	Vascular	240
OR 3B	M	Urology	420	Urology	420	Urology	420	Urology	420	Urology	360
	A	-	0	Urology	240	Urology	240	Urology	240	-	0

5.1.2 HESE Waiting List and MSS

The waiting list of HESE used in the benchmark was provided by the hospital and corresponds to the waiting list in the last day of December 2018. The list comprises 2 437 episodes awaiting surgery, from different specialities. To simplify the list and the model, and according to the provided MSS, specialities *Oftalmologia Retina* and *Oftalmologia* were aggregated as Ophthalmology, *Ortopedia Implante de Próteses*, *Ortopedia Infantil*, *Ortopedia Traumatologia* and *Ortopedia* were aggregated as Orthopedy, OTR and OTR *Infantil* aggregated as OTR and finally, *Urologia* and *Urologia Feminina* as Urology, as can be seen in Table 13.

Table 13 – HESE original surgical specialities, speciality groups, number of surgeons and waiting list information

Original surgical specialities[i]	Speciality group[ii]	No. of surgeons	No. of episodes WL	Avg. surgery duration (min)	Avg. episode due date (days)
Cirurgia Geral	General Surgery	21	711	51,8	33,0
Cirurgia Plástica	Plastic Surgery	3	285	29,5	111,3
Estomatologia	Stomatology	3	14	33,9	-85,5
Oftalmologia	Ophthalmology	14	650	15,7	54,0
Oftalmologia Retina					
Ortopedia Implante de Próteses	Orthopedy	6	240	46,0	42,9
Ortopedia Traumatologia					
Ortopedia					
OTR	OTR	7	301	39,9	-150,6
OTR Infantil					
Urologia	Urology	4	236	37,6	-203,4
Urologia Feminina					

[i] as present in the provided waiting list

[ii] as present in the MSS

The 2 437 episodes are therefore grouped in seven specialities and correspond to 58 surgeons. Although the number of surgeons in each speciality can be greater, the column *No. of surgeons* represents the surgeons responsible for surgery. All entries have an associated forecasted surgery duration based on the patient's pathology and projected procedure, already present in the given waiting list. Furthermore, the due date and priority of each episode is included. The number of days to reach the due date, in the last column, is very low in the case of stomatology, OTR and urology. These negative values mean that in average, the TMRG has already been exceeded by the corresponding number of days. Figure 6 shows the number of episodes out of TMRG per speciality.

The MSS in use for the model is represented in Table 14 and contains two blocks, namely one morning block and one afternoon block for each one of the five ORs in each day. In HESE all blocks have a capacity of 6 * 60 = 360 minutes, except the ones reserved for non-elective patients which were assigned a capacity of zero minutes.

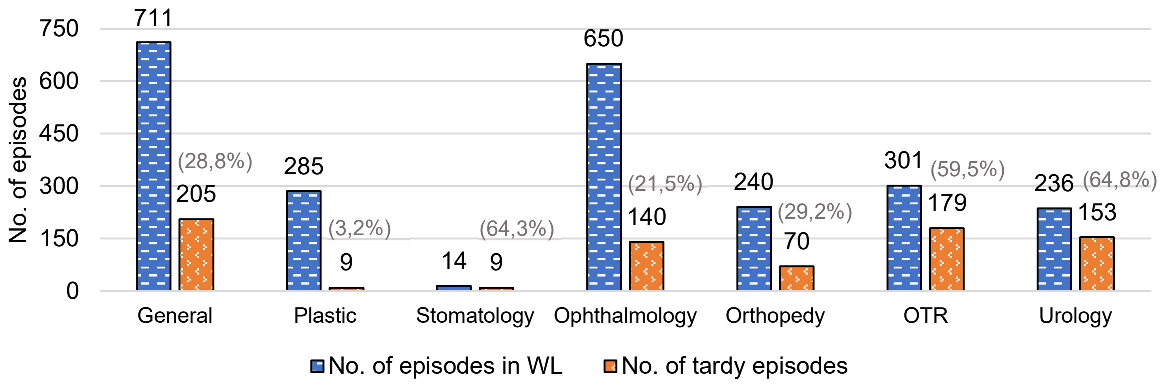

Figure 6 – No. and percentage of episodes in HESE WL out of TMRG

Table 14 – HESE planned MSS and block capacity (minutes)

		Mon		Tue		Wed		Thu		Fri	
OR1	M	General	360	General	360	Ortho	360	General	360	General	360
	A	General	360	General	360	General	360	-	0	-	0
OR2	M	Ortho	360	General	360	Ortho	360	General	360	Stomatology	360
	A	General	360	Plastic	360	-	0	Urology	360	-	360
OR3	M	-	0	-	0	-	0	-	0	-	0
	A	-	0	-	0	OTR	360	OTR	360	-	0
OR4	M	Ortho	360	Ortho	360	Ortho	360	Ortho	360	Ortho	360
	A	-	0	-	0	-	0	-	0	-	0
OR5	M	Ophthalmo	360	Ophthalmo	360	Ophthalmo	360	Ophthalmo	360	-	0
	A	-	0	-	0	-	0	-	0	-	0

5.2 Models' Parameters

Besides the instances and parameters for each hospital, the models themselves also require specific parameters and settings. To perform an accurate benchmark and have the greatest similarity possible between the models tested in this work and the actual models, most parameters used are in accordance with the original papers. However, this was not possible for all parameters, since some assumptions differ, according to the case studies. To summarize all parameters used in the models to perform the benchmark, a table is presented at the end of the section (Table 15).

In Kamran et al. (2018), because the model originally deals with non-elective patients, an occupation parameter to set the block slack is taken into consideration. In this dissertation, the number of non-elective patients is considered zero and therefore all block capacity is used for elective demand with the occupation parameter set to 1. Under the assumption that certain patients need to be hospitalized before the surgery and thus arrive to the hospital some days prior, a release date is also taken into account. The release date is the number of days a patient must wait in preoperative units until surgery can occur. As no data was given on the subject by the hospitals, it is considered that all patients are ready for surgery on the first day of the planning horizon (release date equal to zero for all patients). Regarding the weight of each one of the objective's function terms, the weights used in this work are the same as the weights utilized in the manuscript of Kamran et al. (2018). In Moosavi and Ebrahimnejad (2020) no weights are given as reference for the two objective functions. It is assumed in this work that both have a relative weight of 1.

As no information on the overtime utilization was available, and to reduce the possibility of incurring in overtime, which leads to higher dissatisfaction and cancelation rates, the quantity of overtime is set to be zero. This value is used in all tested models to maintain the coherence not only with the original parameters but also between the different tested models. Also, to maintain the coherence among the models, a cleaning time is defined with a value of 20 minutes. Although the model of Kamran et al. (2018) does not encompass an independent cleaning time, an addition of 20 minutes was made to all surgery durations. Furthermore, as mentioned in the model comparison, both Kamran et al. (2018) and Moosavi and Ebrahimnejad (2020) use a surgery/room utilization time. Marques and Captivo (2017), besides the cleaning time, has two separate parameters for surgery time and room utilization time. This allows the possibility for a surgeon to move to another surgery while the previous patient is still at the room (ex.: the patient is still waiting for the anaesthesia to end but the surgeon is not needed anymore), providing more surgeon rotativity. The rotativity of surgeons, number of surgeries per day or week, can be limited since Kamran et al. (2018) and Marques and Captivo (2017) include a parameter on the maximum capacity of the surgeon, in number of surgeries and minutes of surgery, respectively. These parameters however are considered to be a sufficient large number so no model has restrictions on the surgeons' operating capacity. Regarding the model of Marques and Captivo (2017), the authors employ a penalty factor P for not scheduling surgeries. This penalty factor P is presented in Figure 7. As defined in Section 4.3, the waiting cost (w_c) is calculated as $(dd_c - d_1) * 1{,}2 + P$. As can be seen, episodes out of TMRG – with less than zero days until due date – have a constant penalty of 2000. The penalty value then decreases step-wise until reaching a constant of 50 for episodes with 28 or more days until reaching TMRG. Moosavi and Ebrahimnejad (2020) also considers a waiting cost that does not depend on the patient's waiting time but is equivalent to the priority of the patient. The priorities in consideration are 1, normal, 2, priority, and 3, high priority, for all implemented models. As deferred urgencies, priority level 4, are not accounted for, no non-deferred urgency surgeries are considered in the model of Marques and Captivo (2017), that is, the set $C^{NP} = C$. Similarly, in the model of Moosavi and Ebrahimnejad (2020), no surgery is obligated to be performed in planning horizon, thus the set $IF = \emptyset$. All parameters used at the models' implementation can be found in Table 15.

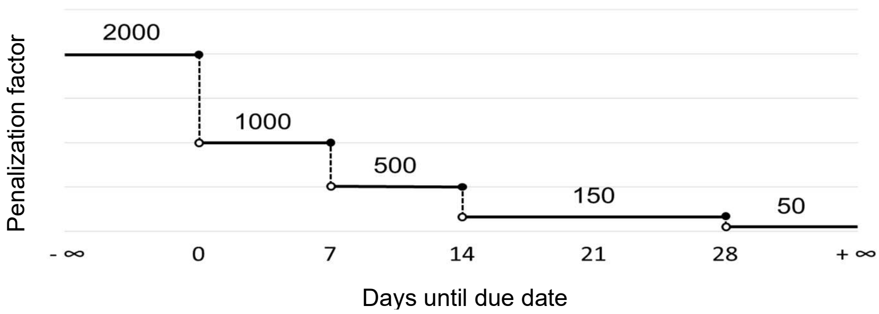

Figure 7 – Penalization factor according to the no. of days until due date

Table 15 – Model parameters specification

Model	Parameter		Value
Kamran et al. (2018)	γ_{bd}	Occupation parameter	1 $\forall b, d$
	A_p	Release date	0 days $\forall p$
	U_p	Clinical priority coefficient	[1, 2, 3]
	m_j	Weight of objective function term	[1; 3; 1; 3; 10; 0,5; 4]
	O_b^{max}	Maximum block overtime	0 min $\forall b$
	O_r^{max}	Maximum room overtime	0 min $\forall r$
	N_s^{max}	Maximum number of daily surgeries per surgeon	10^9 $\forall s$
Marques and Captivo (2017)	t_c^{CLN}	Cleaning time	20 min $\forall c$
	P	Penalization factor	(as seen in Figure 7)
	p_c	Clinical priority	[1, 2, 3]
	k_{hd}^{H}	Maximum daily capacity of surgeon to operate	10^9 min $\forall h, d$
	k_h^H	Maximum capacity of surgeon to operate	10^9 min $\forall h$
Moosavi and Ebrahimnejad (2020)	P_{2jk}	The sterilization time for a surgical case	20 min $\forall j, k$
	TO	Maximum room overtime	0 min
	E_t	Estimate of emergency demand	0
	WC_{jk}	Waiting cost	[1, 2, 3]
	-	Weight of objective function term	[1, 1]

5.3 Chapter Conclusions

The present chapter establishes the instances and parameters to be used for testing the models and perform the benchmark. Regarding the sets of instances, data from both CHLN and HESE are collected and consists of the waiting list from April 16th, 2016 and December 31st, 2018, respectively, and the MSS of each hospital. Whereas the waiting list of HESE already included the mean surgery time for each episode, the surgery times for CHLN episodes are computed from the surgical record of 2013, 2014 and 2015. These estimates can lead to surgery time imprecisions for episodes with only a few homologous entries in the surgical records. Episodes with no homologous entries in the surgical record were removed and correspond to 2,6% of the waiting list. The MSS for the week under study in CHLN is made available, however in HESE, for lack of data, it is considered the current MSS. With respect to the specific parameters of the models, it is important to denote that all the emergency demands are set to zero as only elective patients are studied. Also, to reduce the cancelation rates, an objective of the SNS, overtime and overutilization which leads to higher dissatisfaction and cancelation rates, is also considered zero. Finally, it is worth stating that no limit on the surgeons operating capacity has been imposed, since the adapted model of Moosavi and Ebrahimnejad (2020) does not include a parameter on the subject, and it would create disparities in the results. The following chapter presents the KPIs to evaluate the solutions. The results of the models and a comprehensive discussion are also presented.

6 Results and Discussion

This Chapter presents the benchmark of the three models selected according to the proposed methodology, showing all the obtained results and a further discussion. To evaluate each model's solution in an impartial, side-by-side, comparison, an evaluation matrix is proposed in this work (Section 6.1). The model implementation and computational experiments are introduced in Section 6.2. In Section 6.3 the results obtained by each model in each hospital are presented, followed by a comparative analysis on the selected indicators. The comparative analysis is also performed between the obtained solutions and the actual CHLN schedules for those time instances.

6.1 Evaluation Matrix Formulation

As mentioned previously, the matrix is composed by different KPIs, adjusted to SNS and other stakeholders' objectives, using the work of Penedo et al. (2015) as a basis for the selection of KPIs (Table B1). Similarly to Table B1, the indicators used for the benchmark are gathered in three groups, namely quality, production and productivity (Table 16). It is important to note that some performance indicators such as cost based indicators (Average cost of OR per hour) and standard surgery based (No. of standard surgeries, no. of standard surgeries per adjusted standard surgeon and anaesthesiologist, no. of standard surgeries per OR) from Table B1 are not incorporated since data for surgery costs and surgery type weight respectively was not made available by the hospitals. Furthermore, since this work is focused on elective surgeries, indicators on non-elective surgeries are not studied.

In addition to the KPIs analysed in Penedo et al. (2015) other indicators from each group are considered to evaluate the solutions of each model in a broader spectrum of KPIs. Regarding quality, besides the patient-oriented indicators – percentage of performed surgeries after TMRG, and median of the waiting time – an indicator on the average number of working days per surgeon is included, since the majority of surgeons prefer to have compacted schedules with few working days to allow working in other clinics or hospitals during the rest of the week. In the production group, to complement the no. of elective surgeries and the average utilization of OR time, and considering that a unit of underutilization and a unit of overutilization may not have the same importance for the hospital's administration, the amount of underutilization and the amount of overutilization are also considered. While overutilization time corresponds to the time a room stays open after the regular time whilst a patient is being operated, the underutilization time takes into consideration the regular room capacity (in minutes) minus the total patient utilization and cleaning time of a room. It represents non-working times in-between OR cleaning after surgery and the arrival of the next patient until the closing of the OR. To evaluate the solutions in terms of productivity, the no. of surgeries per OR, per speciality and per surgeon are also incorporated in the matrix.

Table 16 presents all the selected KPIs used in this work to evaluate the solutions and the best value a solution can have for each one. It is worth highlighting that the *best value* in Table 16 and the *value of reference* in Table B1 have no direct correspondence. For instance, the *value of reference* of the percentage of performed surgeries after TMRG (Table B1), selected for a long-term study, is set as lower than 10%. In the case of a one-week scenario, setting the best value to a low percentage on the indicator may imply that surgeries with waiting times higher than the TMRG can be postponed even further. An analogous rationale can be applied for the median of the waiting time of scheduled surgeries, where rewarding the selection of patients with low waiting times in the short-term can lead to higher waiting times in the future. For that reason, a quality indicator on the mean of the waiting time of surgeries that were not scheduled was added, with the best solution being the lowest value possible (LV). Regarding the average no. of working days per surgeon, as mentioned previously, the best solution is the one with the LV.

On the production group, being one of the objectives to schedule as many surgeries as possible, it was considered that the best solution is the one with the highest value (HV) on that indicator. Concerning the utilization of the OR, the best solution is to have 100% occupation rate, with no overutilization time – which is paid differently and increases operational costs – and no underutilization as well. For that reason, both indicators have 0 (minutes) as the best solution possible. In the productivity group, the best solution for the average number of surgeries per dedicated block and per speciality is the HV. Also, when considering the number of surgeries per surgeon, the HV is considered the best solution.

Table 16 – Selected KPIs and best solution value

Group	Indicators	Best solution value
Quality	Percentage of scheduled surgeries after TMRG	HV
	Mean of the waiting time of scheduled surgeries (in days)	HV
	Mean of the waiting time of surgeries not scheduled (in days)	LV
	Average no. of working days per surgeon	LV
Production	No. of scheduled elective surgeries	HV
	Average OR utilization time (in percentage of available OR time)	100%
	Amount of overutilization (in minutes)	0
	Amount of underutilization (in minutes)	0
Productivity	Average no. of surgeries per dedicated block	HV
	Average no. of surgeries per speciality	HV
	Average no. of surgeries per surgeon	HV

In the following section, the results of each individual model are detailed, and the benchmark discussion is performed in accordance with the KPIs developed above.

6.2 Model Implementation and Computational Experiments

To apply the proposed models to the problem under study, all models are coded in Python 3.6.5 with JupyterLab v2.2.6 and are solved using the software IBM ILOG CPLEX 12.10.0, with the usage of the *DoCplex Mathematic Programming* library, version 2.15.194. The initial instances from CHLN and HESE – hospitals' waiting list and MSS – are provided externally through Excel. To process the output solutions, Python is also employed, automatically exporting the needed information to Excel.

The tests were performed in a computer running Windows 10 with an Intel® Core Inside™ i7-6820HQ, four cores, processor of 2.70 GigaHertz and 16 Gigabyte of RAM. In order to achieve feasible solutions in adequate time, similar to a real-life scenario, a time limit of 10 minutes (600 seconds) was established. With the enforcement of a time limit, most models did not reach the optimal solution, presenting a feasible solution and the respective gap. In the remaining of this dissertation, the models of Kamran et al. (2018), the administration's, the surgeons' and the mixed version of Marques and Captivo (2017), and the model of Moosavi and Ebrahimnejad (2020) are also referred as *KKD*, *MC.Admin*, *MC.Sur*, *MC.Mix*, and *ME* respectively. The mentioned terms and the authors' name are used interchangeably. Table 17 shows the score of the best solution found in the established time and the corresponding solution gap for both case studies. The number of patients in the waiting list and the number of blocks for each hospital is also presented.

Table 17 – Solution values and gap comparison over models and case studies (time limit of 10 minutes)

	CHLN					HESE				
No. of episodes in WL	3 033					2 437				
No. of blocks in MSS	43					29				
	KKD	**MC.Admin**	**MC.Sur**	**MC.Mix**	**ME**	**KKD**	**MC.Admin**	**MC.Sur**	**MC.Mix**	**ME**
Solution Value	431154	774467	630141	775312	132328	551728	578521	380038	592552	169290
Gap	0,00%	0,07%	0,01%	0,07%	0,60%	0,00%	0,02%	0,09%	0,03%	0,02%

The model of Kamran et al. (2018) was able to achieve an optimal solution in both scenarios. When comparing the results, the value of the achieved solution for any model has no significance as each objective function is different. As would be expected, since the case study of HESE comprises a smaller waiting list and lesser blocks in the MSS, the gap reached in the HESE scenario is generally smaller for the same models, except in the surgeons' version of Marques and Captivo (2017) model, where a gap of 0,01% and one of 0,09% in CHLN and HESE was achieved, respectively.

In the following section, the results for each model are presented in detail, alongside a discussion on the results. All models are tested in accordance with the instances and parameters given in Chapter 5, except when stated. In this specific case, the used parameters and all needed information is detailed.

6.3 Case Studies Results and Discussion

After testing the models with three small instances and guaranteeing the feasibility of the solutions, the models were tested with the instances from CHLN and HESE. To display the results in a coherent manner, all tables are ordered, presenting for any indicator firstly a table with the results for CHLN case study and then a table for HESE case study's results. As mentioned earlier, the tests correspond to the week of 18th to 22nd of April 2016 in the case of CHLN and the first week of 2019 – December 31st, 2018 to January 4th, 2019 – in the case of HESE. Regarding the case of HESE, no holidays have been considered since the objective is to reproduce a generic week from Monday to Friday, and real data from HESE for the week in consideration, besides the waiting list, has not been provided. On the other hand, in the case of CHLN, the actual surgery plan for the week is given This CHLN surgery plan comprise the actual planned scheduling for the week. As no time indication was given in the scheduling plan, and to fairly compare with the models' findings, the same average utilization times using the data from 2013 to 2015 were used. The results achieved in the tests are compared with the provided plan whenever possible. In Subsection 6.3.1, different performance indicators and findings of the models are described and discussed, individually, both for CHLN and HESE. Subsection 6.3.2 establishes the integrated table of KPIs, presenting a holistic comparison of the models' outcome.

6.3.1 Intra-indicators Analysis

As can be seen in Table 18, all models have successfully scheduled patients from a total of 3 033 patients from the waiting list. The model with more scheduled surgeries is Marques and Captivo (2017) surgeons' version – MC.Sur – with 109 episodes scheduled, one more than the Kamran et al. (2018) – KKD – model's 108 scheduled episodes. Afterwards, in decreasing order, MC.Mix, MC.Admin and finally ME with 92 scheduled episodes. All results show that the models are able to schedule more surgeries than CHLN surgical plan, however, it is important to note that the used parameters and assumptions under which the models were run are estimates and therefore, although close to reality, they have variations from the real scenario. For these reasons, the expected production values from the CHLN surgical plan are used as guidelines and cannot be compared directly. MC.Sur, despite having the best performance on the overall number of scheduled patients, schedules only priority 1 patients, having zero priority 2 and 3 scheduled patients. To the hospital's administration and patients themselves this can have serious impacts since priorities 2 and 3 are more urgent than priority 1. With exception for MC.Sur and ME, which only schedules two episodes of priority 2 and one of priority 3, all the other models are very consistent between them, with 13, 14 and 13 priority 2, and 14, 16 and 16 priority 3 episodes scheduled in models KKD, MC.Admin and MC.Mix respectively. These results – higher number of priority 2 and 3 scheduled episodes in models KKD, MC.Admin, MC.Mix and ME when compared to MC.Sur – are within the expected as MC.Sur is the only model that does not consider the priority level of the surgeries, with the exception of deferred urgency surgeries not addressed in this work.

Table 18 – Scheduled surgeries per priority at CHLN

	Total in WL	Scheduled					
		CHLN	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Priority 1	2 949	63	81	63	**109**	71	89
Priority 2	63	16	13	**14**	0	13	2
Priority 3	21	3	14	**16**	0	**16**	1
Total	3 033	82	108	93	**109**	100	92

Considering the total number of scheduled patients, the findings from HESE are in accordance with the scenario from CHLN. In the case of HESE, from 2 437 episodes in the waiting list, the model MC.Sur is also the one with more episodes scheduled, 274 episodes (Table 19). Although the number of blocks in HESE is lesser than in CHLN (Table 17), a shorter average surgery time for HESE surgeries – 36,0 minutes compared with 169,3 minutes – is held as the reason for the higher number of scheduled patients by all models. In the case study of HESE, by decreasing order of scheduled episodes, we have

MC.Sur (274), KKD (268), MC.MIX (242), ME (238) and finally MC.Admin (230). Both MC.Sur and KKD have the highest number of scheduled episodes, with a difference of only one patient (109 to 108) in CHLN and six patients (274 to 268) in HESE. MC.Admin and ME got the lowest number of scheduled episodes, with a difference of one patient (93 to 92) and eight patients (238 to 230) in CHLN and HESE, respectively. Although ME falls again in the second worst result on scheduled episodes with priority 2 and 3, their actual number has increased in HESE, by contrast with the low results of CHLN. Hence, these variations indicate that using only one or two case studies, or sets of data, to determine the quality of a model is not sufficient, as the result can differ with other instances. Ideally, only by using sufficiently large sets of different data, is it possible to get robust results. In this work all results are analysed using only two case studies, therefore, although having some predictability, it is not possible to prove that the models will behave in the same way for a third or fourth instance.

Table 19 – Scheduled surgeries per priority at HESE

	Total in WL	Scheduled				
		KKD	MC.Admin	MC.Sur	MC.Mix	ME
Priority 1	2 178	180	127	**266**	117	187
Priority 2	211	43	57	8	**81**	20
Priority 3	48	45	**46**	0	44	31
Total	2 437	268	230	**274**	242	238

According to SNS, a different TMRG is assigned to each priority, and the sorting of the waiting list must be done by the priority and the number of days until TMRG/due date (see Section 2.3.2). It implies that, if well sorted, and if surgeons select patients based on that parameter, patients from the same priority group are selected by their waiting time. However, through Table 20, which presents the number of tardy scheduled surgeries (already passed TMRG) versus total number of scheduled surgeries, it is possible to infer that patients are not selected according to this parameter. As expected, MC.Sur mimics the surgeons' scheduling behaviour, although being more extreme, with no tardy patient selected in comparison with ten patients selected in CHLN surgical plan for the week in consideration (Table 20). On the other end, the model of Kamran et al. (2018) schedules 86 tardy patients. Despite being in second in terms of absolute number of tardy scheduled episodes (76 patients), the results of MC.Admin show the highest percentage between scheduled tardy patients and total scheduled patients (81,72%) compared with KKD (79,63%). Being a hybrid model between MC.Admin and MC.Sur, as discussed before, MC.Mix has a clear improvement on the resulted of the later, almost reaching the result of the former. One possible reason for the surgical plan of CHLN low number of tardy scheduled patients and high number of patients scheduled within TMRG when other tardy episodes exist may have to do with internal SNS objectives. In the payment contracts established between the SNS and the hospitals, one of the used metrics to assess the quality of the service is the target number of surgeries performed within TMRG. As mentioned before, this and similar metrics may promote the selection of episodes that are within TMRG and postpone even further the ones that already passed may be prompted. The results of ME using CHLN instances show a balance between tardy scheduled episodes and in-time scheduled episodes, having almost 45% tardy and 55% in-time episodes.

Table 20 – Tardy scheduled surgeries per speciality at CHLN

Tardy | Total Sched.	Total in WL	Scheduled					
		CHLN	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Total	943 | 3 033	10 | 82	**86** | 108	76 | 93	0 | 109	71 | 100	41 | 92
Percentage	31,10%	12,20%	79,63%	**81,72%**	0,00%	71,00%	44,57%
General Surgery	53 | 526	0 | 34	28 | 38	24 | 35	0 | 40	21 | 39	11 | 32
Orthopedy	341 | 894	6 | 10	22 | 26	18 | 20	0 | 26	18 | 20	10 | 25
Urology	100 | 572	3 | 23	22 | 28	22 | 22	0 | 28	20 | 25	16 | 22
Vascular Surgery	449 | 1 041	1 | 15	14 | 16	12 | 16	0 | 15	12 | 16	4 | 13

When observing the results of the same models using the HESE instances (Table 21), the panorama is very similar to CHLN, with the only exception of ME. In this case, the highest overall number of tardy scheduled surgeries (222) is seen in the model ME, also being the highest in relative terms (93,28%). This different behaviour shows that, by changing the testing samples, findings can be different and only with an average over a large number of sets of data, extrapolations can become more secure. Besides ME, all the other results are coherent with the ones in the table above (Table 20) – KKD has the highest number of tardy scheduled episodes, even though MC.Admin has a higher ratio between tardy and total scheduled episodes. MC.Sur, has only one tardy patient scheduled, whereas MC.Mix improves this value, reaching almost the number of tardy patients scheduled by MC.Admin (162 in MC.Mix, compared with 180 in MC.Admin, a difference of 1%). Unfortunately, the surgical plan of HESE for the week under study was not provided, so a comparison with their data is not possible.

Table 21 – Tardy scheduled surgeries per speciality at HESE

Tardy | Total Scheduled	Total in WL	Scheduled				
		KKD	MC.Admin	MC.Sur	MC.Mix	ME
Total	765 | 2 437	185 | 268	180 | 230	1 | 274	162 | 242	**222** | 238
Percentage	31,39%	69,03%	78,26%	0,36%	66,94%	**93,28%**
General Surgery	205 | 711	53 | 80	52 | 68	0 | 90	42 | 72	67 | 70
Ophthalmology	140 | 650	51 | 66	50 | 57	0 | 66	48 | 58	60 | 63
Orthopedy	70 | 240	38 | 65	40 | 53	0 | 63	40 | 53	47 | 53
OTR	179 | 301	24 | 31	22 | 24	1 | 28	17 | 31	28 | 28
Plastic Surgery	9 | 285	3 | 9	0 | 12	0 | 12	0 | 12	4 | 7
Stomatology	9 | 14	7 | 7	7 | 7	0 | 5	7 | 7	6 | 7
Urology	153 | 236	9 | 10	9 | 9	0 | 10	8 | 9	10 | 10

The actual scheduling profile of the CHLN's and each model's surgical plan can be seen in Figure D.1 (Appendix D), organized by the number of days until due date – a negative number means that the TMRG has already been passed. Figure D.2 (Appendix D) shows the scheduling profile of each model as well for the instances of HESE. Figure 8 and Figure 9 comprise the distribution of tardy scheduled patients for both hospitals. It is important to denote that the patients are grouped by number of days out of TMRG and, for scaling reasons, because the higher the number of days out of TMRG, the lesser the number of episodes, the grouping interval also changes. There are four groups comprising 25 days each between -1 and -100 days, eight groups of 50 days between -101 and -500 and five groups of 100 days from -601 to -1001. In the case of CHLN, as the patient with higher waiting time has passed 1087 days from TMRG, one group of 500 days between -1001 and -1500 was set. HESE on the contrary, has patients with higher waiting times which require an additional group from -1501 and -2000. The dotted line in each figure represents the median of days out of TMRG for tardy patients in the waiting list. In CHLN's case (Figure 8), 50% of tardy patients are 91 days or less out of TMRG, while the other 50% are 92 or more days out of TMRG. An analogous procedure is made for HESE's case (Figure 9), being the median of the waiting time out of TMRG 112 days.

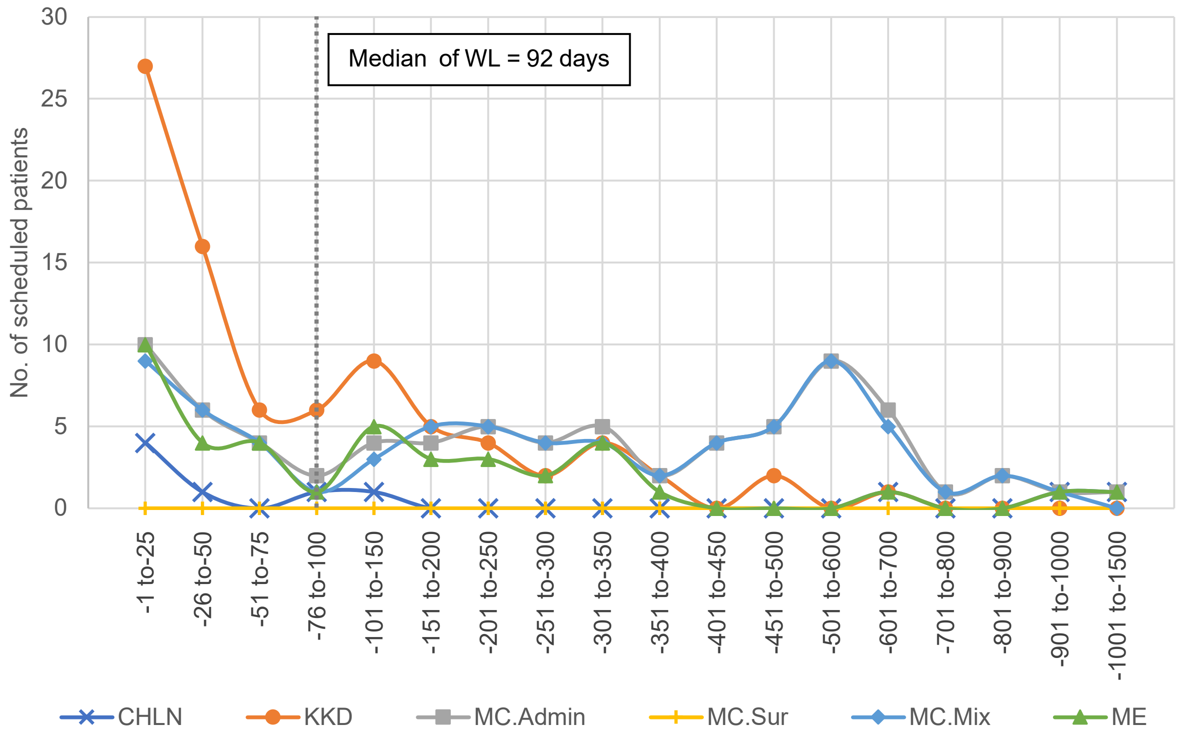

Figure 8 – Distribution of scheduled patients in CHLN by no. of days out of TMRG

Observing Figure 8, it is possible to see the distribution of scheduled patients per number of days out of TMRG. Contrasting with all other model's solutions, MC.Sur, which does not schedule tardy patients, and the CHLN plan, with 10 tardy patients scheduled, are the ones with the least number of tardy scheduled patients. Also, according to CHLN plan's distribution, more emphasis is given to patients that have recently passed the due date, than patients with higher waiting times (six scheduled patients between zero and -100 days, and 4 patients between -101 and -1500 days). Linear correlation between the findings for CHLN case are presented in Table 22, both for non-grouped findings and for the groups presented in Figure 8. The linear correlations are established based on the number of patients scheduled by number of days out of TMRG. When studying the other models' distributions, there is a higher correlation between Marques and Captivo (2017) administration's and mixed versions (0,959). This is already expected since the models share part of the objective function and constraints. Both models focus on scheduling patients with higher waiting times, scheduling approximately 70% of their tardy patients with between 100 and 1500 days out of TMRG. The reason for scheduling more patients with higher waiting times lays on the large penalty in the models' objective function which comprises a penalty value and a virtual extension of the patient's waiting time by the factor of 1,2. Furthermore, knowing that the waiting list has more patients with smaller waiting times, the low correlation between the findings of both MC.Admin and MC.Mix, and the waiting list itself, shows that these models do not follow the list properties, selecting more patients with higher waiting times.

When examining the grouped results, as shown in Figure 8, between Kamran et al. (2018) and Moosavi and Ebrahimnejad (2020) there is also a high linear correlation (0,904). Through Table 22 it is possible to see that these two models follow a more approximate distribution of the CHLN waiting list. As would be expected, since there is a vast list of patients out of TMRG, all correlations increase with the creation of groups. As no tardy patient is scheduled, it is not possible to calculate linear correlations for the findings of MC.Sur in CHLN.

Table 22 – Correlations between WL, CHLN plan and models' results for CHLN case (days out of TMRG)

(i)	WL	CHLN	KKD	MC.Admin	MC.Sur	MC.Mix	ME
CHLN	0,239	1					
KKD	0,575	0,237	1				
MC.Admin	0,278	0,181	0,498	1			
MC.Sur	-	-	-	-	-		
MC.Mix	0,262	0,152	0,485	**0,959**	-	1	
ME	0,410	0,209	0,514	0,323	-	0,256	1
(ii)	**WL**	**CHLN**	**KKD**	**MC.Admin**	**MC.Sur**	**MC.Mix**	**ME**
CHLN	0,593	1					
KKD	0,845	0,806	1				
MC.Admin	0,401	0,430	0,586	1			
MC.Sur	-	-	-	-	-		
MC.Mix	0,355	0,309	0,526	**0,975**	-	1	
ME	0,782	0,720	0,904	0,544	-	0,475	1

(i) With no grouping. (ii) According to the groups presented in Figure 8.

As mentioned, Figure 9 shows the distribution of scheduled patients per number of days out of TMRG for each model using HESE's instances. Very similar to what has been observed in CHLN scenario and as expected, the results of the surgeons' version of Marques and Captivo (2017) show the worst performance with only one tardy scheduled patient, in the range from -1 to -25 days out of TMRG. Regarding the findings of all other models, and in opposition to the CHLN case, a stronger correlation is clear. These correlations, which can be confirmed in Table 23, suggest that when grouping is performed, the values of the respective correlations increase drastically. When no grouping is done, the results of MC.Admin and MC.Mix present the highest correlation in terms of tardy scheduled patients (0,924). Despite the high correlation between all models' findings – except for MC.Sur – it possible to see in Figure 9 that until the waiting list's median of days out of TMRG (112 days), both KKD and ME, and MC.Admin and MC.Mix present a similar curve, with the last two scheduling only 55% of the first two between -1 and -112 days out of TMRG. However, after the median, both MC.Admin and MC.Mix schedule more patients than KKD and ME, showing again the model's preference for selecting patients with higher waiting times. In fact, whereas KKD and ME schedule respectively 29,2% and 35,6% of tardy patients with more than 112 days out of TMRG, which equals 54 and 79 patients selected, MC.Admin and MC.Mix schedule 59,4% and 51,2% of tardy patients with more than 112 days out of TMRG, which equals 107 and 80 patients, respectively.

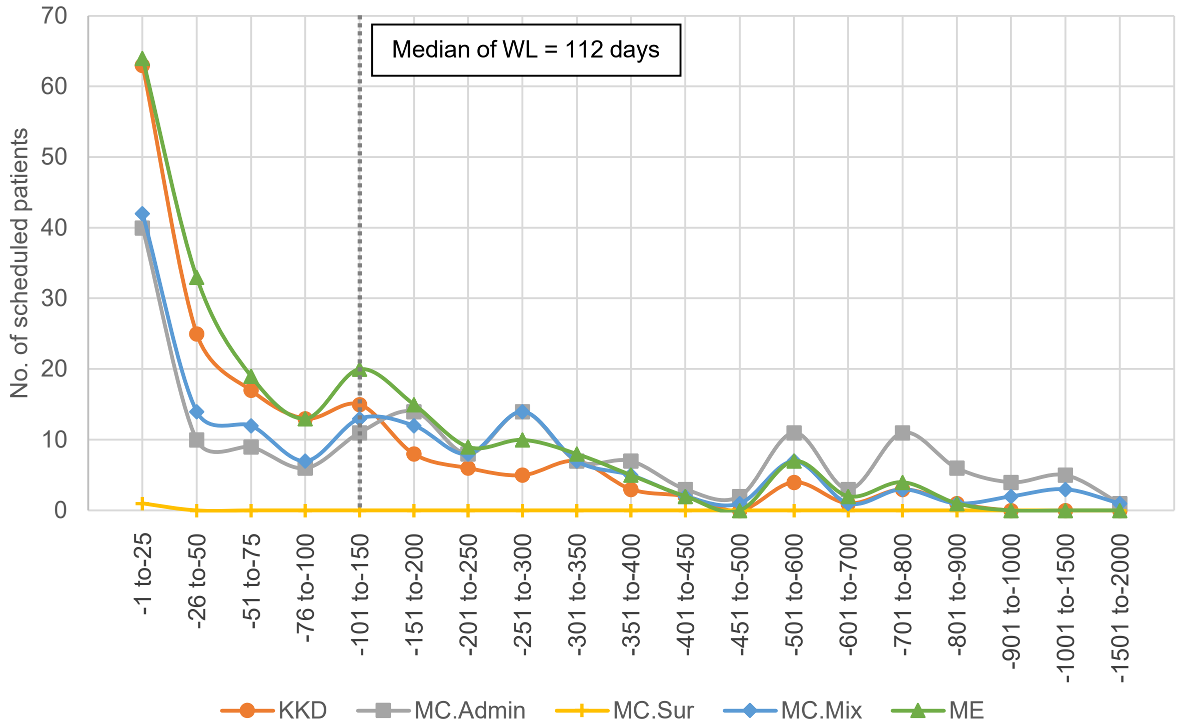

Figure 9 – Distribution of scheduled patients in HESE by no. of days out of TMRG

Table 23 – Correlations between WL and models' results for HESE case (days out of TMRG)

	(i)						(ii)					
	WL	**KKD**	**MC.Admin**	**MC.Sur**	**MC.Mix**	**ME**	**WL**	**KKD**	**MC.Admin**	**MC.Sur**	**MC.Mix**	**ME**
KKD	0,721	1					0,941	1				
MC.Admin	0,605	0,801	1				0,829	0,897	1			
MC.Sur	0,080	0,082	0,046	1			0,716	0,884	0,880	1		
MC.Mix	0,656	0,855	**0,924**	0,100	1		0,922	0,953	0,960	0,851	1	
ME	0,760	0,845	0,714	0,036	0,747	1	0,970	**0,989**	0,896	0,826	0,963	1

(i) With no grouping. (ii) According to the groups presented in Figure 9.

Selecting patients with higher waiting times leads to a waiting list of patients with lower waiting times. However, analysing only the number and distribution of tardy patients, or the absolute number of tardy scheduled surgeries is not sufficient to understand how the waiting list for the next planning horizon is going to be. Being the TMRG the maximum response time for operation guaranteed by the SNS, the objective is to have the least percentage of episodes out of TMRG in the waiting list, when observing a long-term scenario. Excluding the demand that arises in-between the planning horizons (i.e. considering the waiting list from the current planning horizon minus the scheduled episodes) it is necessary to know the average of days until TMRG (or waiting time) for the scheduled surgeries to compute the average of days until TMRG for the surgeries not scheduled. In the following Table 24 it is possible to observe how the average of days until TMRG for surgeries not scheduled varies accordingly to the value for scheduled surgeries in CHLN scenario. To help the reader, the values on the total number of scheduled episodes, tardy scheduled episodes and the number of episodes remaining in the waiting list are depicted as well. MC.Sur, despite having more surgeries scheduled has the lower average of days until TMRG (which corresponds to a higher waiting time), since no tardy surgeries are selected, and the selected surgeries have a very low waiting time. KKD's results, for instance, despite having the highest number of tardy episodes scheduled, also fall behind MC.Admin results, with the highest average of days until TMRG (or lowest average waiting time in the waiting list). Attending to the evolution of the waiting list it is important to consider both the quantity of scheduled episodes, which represents the outflow of patients, and the waiting time of patients that remain in the waiting list, which relates to the scheduling order followed by the surgeons.

Table 24 – Average of days until TMRG for scheduled and non-scheduled surgeries at CHLN

	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Avg. of days until TMRG for:					
Scheduled surgeries	- 67,88	- 252,91	162,54	- 203,76	- 25,33
Surgeries not scheduled	36,63	**41,95**	28,08	40,98	34,73
No. of scheduled episodes	108	93	**109**	100	92
No. of tardy episodes scheduled	**86**	76	0	71	41
Episodes remaining in the WL	2925	2940	**2924**	2933	2491

As portrayed for CHLN scenario, the results for HESE's instances on the average of days until TMRG for both scheduled surgeries and surgeries not scheduled (remaining in waiting list) are presented in Table 25. By selecting patients with very short waiting times, mainly through the expected Last-in-First-out order of scheduling, MC.Sur has the worst performance in terms of average of days until TMRG (-14,24), despite selecting more episodes among all other models. Actually, it is the only model where the remaining waiting list has a negative value on the indicator, meaning that in average, patients who have not been scheduled, have passed the TMRG by 14 days.

Table 25 – Average of days until TMRG for scheduled and non-scheduled surgeries at HESE

	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Avg. of days until TMRG for:					
Scheduled surgeries	-50,70	-221,93	134,58	-123,90	-120,80
Surgeries not scheduled	9,06	**25,88**	-14,24	16,42	15,83
No. of scheduled episodes	268	230	**274**	242	238
No. of tardy episodes scheduled	185	180	1	162	**222**
Episodes remaining in the WL	2169	**2207**	2163	2195	2199

On the opposite side, MC.Admin, although scheduling the least number of episodes (16% less than the results of MC.Sur), has the best performance on the average number of days until TMRG. The focus on scheduling episodes with the highest waiting times allows to have an average of 25 days until TMRG for patients remaining on the waiting list. Nevertheless, as mentioned for the previous scenario, it is important to understand that attending only to one indicator – whether it is the number of scheduled episodes, the tardy episodes or the average number of days until TMRG – may compromise the overall result. In this particular case, the model that schedules more surgeries (best patient outflow rate), leaves the patients with higher waiting times in the list, and vice versa: the model responsible for scheduling patients with higher waiting times, falls behind of the other models in the number of scheduled episodes. While no correlation is being suggested, it is always necessary to have a holistic overview of the results on each indicator. For example, the findings of ME show that, in terms of total number of scheduled surgery and the number of tardy episodes scheduled there was an improvement of 3,5% and 23,3% respectively, when compared to MC.Admin, but there was an increase of 10 days in the average waiting time of the waiting list. MC.Mix, developed as a "middle-ground" model between MC.Admin and MC.Sur, has a very good performance overall in the subject, being able to schedule 5,2% more episodes than MC.Admin. And although it only schedules 162 patients out of TMRG (being in fourth place), it accomplishes the second-best average on days until TMRG (16,42 days).

Besides the effective number, priority and tardiness/lateness of the scheduled episodes, the efficient utilization of OR resources is crucial for expenditure control, one main concern at the management level. On the one hand, since the staff is paid taking into consideration the number of hours per block, in the case of underutilization of ORs and personnel, it implies the payment of time with no productivity. On the other hand, blocks can also incur in overtime. Depending on the quantity of overtime, surgeries for the same day in the OR can be delayed or even cancelled. For cancelled surgeries there is a necessity to postpone and reschedule them in the following days, which leads to additional costs. As main stakeholders in the surgery environment, changes in the surgery schedule are detrimental for patients that have to adapt their agenda without any advance notice. Furthermore, for the hospitals' administrations it is an additional expense since all personnel is paid an extra fee during the overtime hours. For both CHLN and HESE scenarios, the utilization of overtime is restricted in the models' parameters and only underutilization can occur. While it is true that an 100% expected utilization of the OR (surgery and necessary cleaning time per surgery) may lead to low flexibility for unpredicted delays, the chosen parameter for occupation was 1 (see Section 5.2). If the hospitals' administrations opt to have a buffer, the parameter can be easily set.

In Table 26 it is possible to see the findings on utilization time for each model, using CHLN data. The values for CHLN plan are also presented. As mentioned and to perform a fair comparison, all values are calculated according to the number and type of scheduled surgeries and the predicted duration of surgeries using the references of 2013 to 2015. As expected, all models have under 100% occupation rates, however, the models have different degrees of underutilization. In CHLN, MC.Mix accomplishes the best result with less than 400 minutes in total (sum of all blocks). These represent an average of 9,3 minutes of underutilization per working block, a difference of -2,6% of the total block duration. It is interesting to denote that in this parameter the mixed version of Marques and Captivo (2017) is not in between the findings of MC.Admin and MC.Sur. Actually, the total undertime for MC.Admin is 428,1 minutes (an increase of 7,2% from MC.Mix) and MC.Sur has the worst result over all models with 727,5 minutes of underutilization (an increase of 82,1% compared to MC.Mix). The findings of KKD show a very similar result to MC.Sur (716,4 minutes). Despite the difference on the amount of total underutilization being 82% from best to worst result ($82\% = \frac{(best\ score - worst\ score)}{best\ score}$), the difference of the results, when analysing the values translated in percentage of OR occupation becomes more subtle. As mentioned, the best result on underutilization is of model MC.Mix, with 399,5 minutes, accomplishes an OR occupation rate of 97,4% and the model with the worst result on undertime, MC.Sur, with 727,5 minutes, has an OR occupation rate of 95.3%.

Table 26 – Underutilization and occupations of CHLN blocks

	CHLN Plan	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Underutilization	-166,8	716,4	428,1	727,5	**399,5**	633,0
General	-1 269,4	201,4	154,9	59,0	80,9	143,0
Orthopedy	1 227,8	148,0	95,6	34,8	95,6	67,0
Urology	-279,0	113,7	15,5	18,0	60,9	64,0
Vascular	153,8	253,3	162,0	615,7	162,0	359,0
Avg. Underutilization per block	-3,9	16,7	10,0	16,9	**9,3**	14,7
General	-84,6	13,4	10,3	3,9	5,4	9,5
Orthopedy	122,8	14,8	9,6	3,5	9,6	6,7
Urology	-34,9	14,2	1,9	2,3	7,6	8,0
Vascular	15,4	25,3	16,2	61,6	16,2	35,9
OR Occupation Rate	101,1%	95,4%	97,2%	95,3%	**97,4%**	95,9%
Avg. Occupation Time w/ CT	363,6	343,3	350,0	343,1	**350,7**	345,3
Avg. Occupation Time w/o CT	325,5	293,1	**306,8**	292,4	304,2	302,5

On the opposite side, the CHLN Plan has a negative value for underutilization as can be seen in the table, which is equivalent to 166,8 minutes of overutilization. However, despite having an average OR occupation rate of only 101,1% (average of 3,9 minutes of overtime per block), the plan has the largest discrepancies among specialities (1 269,4 minutes of overutilization in general surgery to 1 227,8 minutes of underutilization in orthopedy). For instance, when accounting for single specialities, the CHLN plan has an average OR occupation rate of 76,5% for general surgery and 134,1% for orthopedy. As can be seen from all models' findings, the usage of an optimization software would decrease the underutilization and its variation among specialities while reducing misjudgements on surgery durations and allowing the possibility for buffers if needed.

In Figure 10 it is possible to compare the average occupation with and without the respective cleaning time for each surgery. The deviations from the average block duration are also depicted in percentage. The CHLN plan is the only with an expected occupation higher than the block duration (+1,1%). For the CHLN plan no data was given on the predicted cleaning time by each surgeon when scheduling and for that reason, the average of 20 minutes, recommended by Penedo et al. (2015), and used for the model's parameters is used as well in CHLN plan. Interestingly, for the models, it is shown that the occupations without cleaning time are not directly proportional to the occupancy with cleaning time. To give an example, MC.Admin which is second in terms of occupation time with cleaning (-2,8%), comes in first in the parameter of occupation time without cleaning time (-14,8%). This difference is related with the number of surgeries per block. With a constant cleaning time for each surgery, the higher the number of surgeries, the higher the total cleaning time per block. The average occupation without cleaning time in the results of MC.Sur has the lowest performance with 292,4 minutes (-18,8%). The gap between the best and worst results regarding average occupation time with cleaning time is 7,6 minutes and 14,4 minutes without cleaning time. While it might seem a small difference among the models, when considering the total of 43 blocks per week and the respective value for one year, the difference is considerably higher.

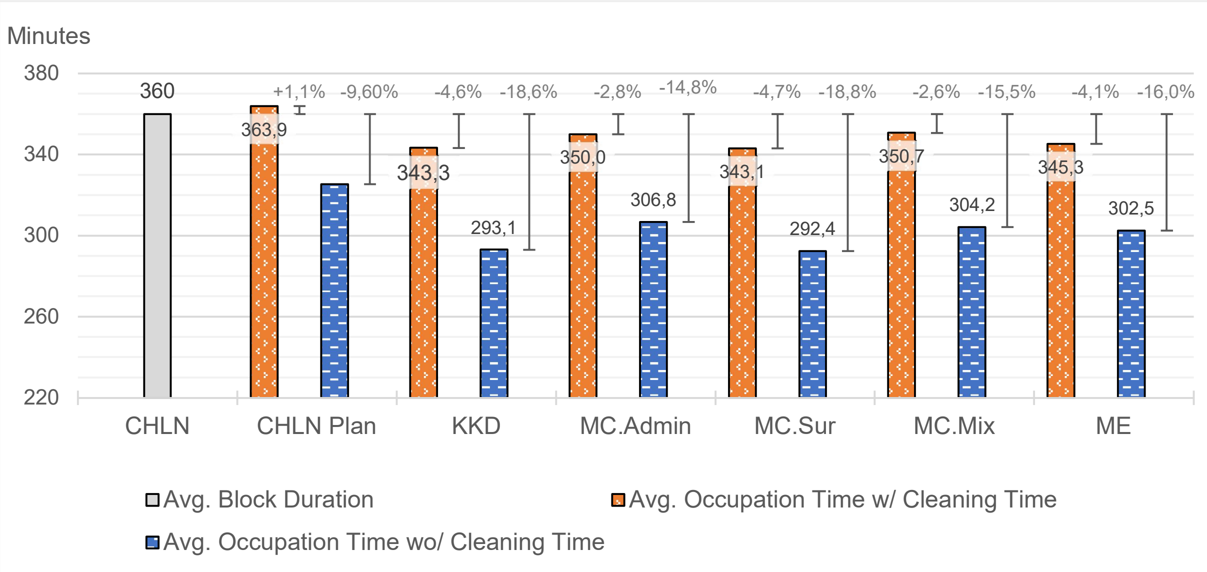

Figure 10 – Average occupation times with and without room cleaning time per block for CHLN

The findings using HESE data show a better use of the capacity, with a significant reduction of under-utilization (Table 27) for the same average block length of 360 minutes. One of the factors which can contribute for such a difference is the reduced number of blocks (43 blocks in CHLN compared with 29 in HESE), however, when analysing the average underutilization per block, results show that the values for HESE are still smaller, when compared with CHLN. Being so, it is presented the possibility that by having much shorter surgery durations compared to CHLN (as mentioned in Section 5.1, the average duration of surgeries is 36,0 minutes in HESE and 169,3 minutes in CHLN), more combinations of different episodes that provide lesser block undertime utilization are possible in HESE. As can be denoted in Table 27, both MC.Admin and MC.Mix – which have the best results in CHLN case – present the same underutilization of 30 minutes (average of one minute per block), although distributed in distinct ways across specialities. In this scenario, the model of Moosavi and Ebrahimnejad (2020) has the best result with an underutilization of 19 minutes, that translates in less than a minute of underutilization per block and a OR occupation rate of 99,82%. KKD and MC.Sur present still the worst results on the parameter, with 147 and 114 minutes of underutilization, respectively. Nonetheless, the high values of underutilization from these two in comparison with the other models, represent only a variation of -1,4% and -1,1% from the average block duration (Figure 11). Since all models are able to schedule more episodes using HESE instances, more cleaning cycles are needed per block. Hence, in Figure 11, it is clear that percentages between occupation with and without cleaning time for each model present higher differences.

Table 27 – Underutilization and occupations of HESE blocks

	KKD	MC.Admin	MC.Sur	MC.Mix	ME
Underutilization	147,0	30,0	114,0	30,0	**19,0**
General	69,0	11,0	11,0	15,0	5,0
Plastic	5,0	0,0	0,0	0,0	0,0
Stomatology	10,0	10,0	75,0	10,0	5,0
Ophthalmology	3,0	1,0	9,0	3,0	8,0
Orthopedy	48,0	1,0	6,0	1,0	1,0
OTR	2,0	0,0	4,0	1,0	0,0
Urology	10,0	7,0	9,0	0,0	0,0
Avg. Underutilization	5,1	1,0	3,9	1,0	**0,7**
General	6,9	1,1	1,1	1,5	0,5
Plastic	5,0	0,0	0,0	0,0	0,0
Stomatology	10,0	10,0	75,0	10,0	5,0
Ophthalmology	0,6	0,2	1,8	0,6	1,6
Orthopedy	6,0	0,1	0,8	0,1	0,1
OTR	0,7	0,0	1,3	0,3	0,0
Urology	10,0	7,0	9,0	0,0	0,0
OR Occupation Rate	98,59%	99,71%	98,91%	99,71%	**99,82%**
Avg. Occupation Time w/ CT	354,9	359,0	356,1	359,0	**359,3**
Avg. Occupation Time w/o CT	170,1	**200,3**	167,1	192,1	195,2

The best result comes from the model MC.Admin, that although having the same occupation time with cleaning time than MC.Mix, as mentioned, has more 8,2 minutes of average occupation per block when no cleaning time is considered. The findings show that ME has the second-best value with a difference of 5,1 minutes from MC.Admin. MC.Sur has the worst result with less than 50% of average block occupation time without cleaning time. Again, one trade-off worth noticing is that the amount of cleaning time is proportional to the number of scheduled surgeries. From the data of both indicators – average occupation time with and without cleaning time –, it possible to conclude, for instance, that MC.Mix does schedule more patients than MC.Admin and ME, as well as MC.Sur when compared to KKD.

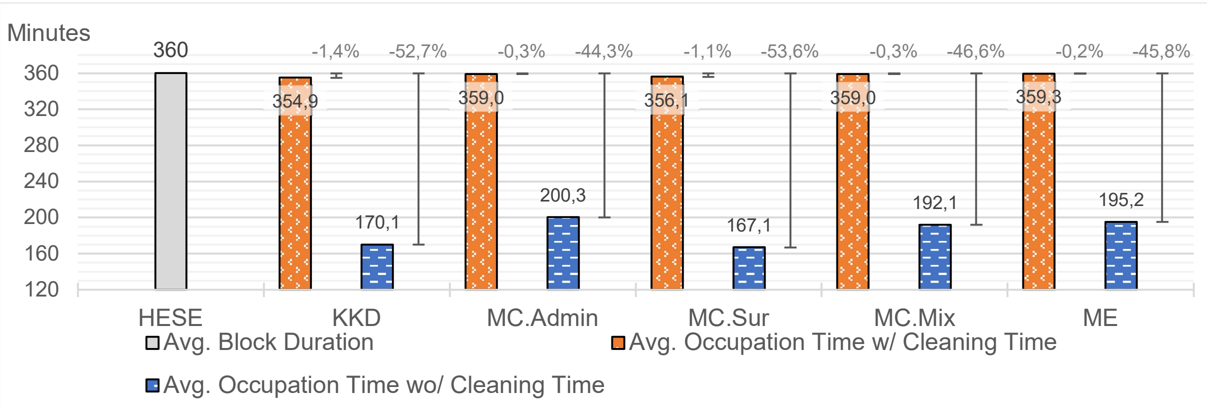

Figure 11 – Average occupation times with and without room cleaning time per block for HESE

For surgeons, the daily block occupation without cleaning time has more relevance and importance since they are not needed in the cleaning process. However, the major concern among surgeons is not the daily workload, but the number of working days that they are required to perform surgeries. As mentioned in Section 6.1, surgeons prefer to condense the workload in one or few days to have flexibility in the rest of the week to work in other hospitals or clinics. Being one of the most important stakeholders on the surgery process, and the ones responsible for scheduling the surgeries in the current SNS hospitals' practice, the interests of surgeons have also to be sought in any scheduling optimization model. Described in Section 4.5, Kamran et al. (2018) is the only paper that incorporates the objective of reducing the number of surgeon's working days. In fact, having in consideration the findings presented in Table 28, for CHLN, and Table 29, for HESE, KKD presents the best results in terms of average number of working days per surgeon. It is important to mention that this average only takes into consideration surgeons that are planned for the week. Therefore, surgeons whose surgeries are not scheduled (with zero working days) are not accounted.

Table 28 – Surgeon utilization per speciality at CHLN

	Total in WL	Scheduled					
		CHLN	KKD	MC.Admin	MC.Sur	MC.Mix	ME
No. of Surgeons	148	42	46	49	49	53	45
General	48	16	12	13	18	15	17
Ortho	30	10	12	12	10	12	14
Urology	31	8	12	12	17	14	8
Vascular	29	8	10	12	4	12	6
Avg. No. WD per Surgeon	-	1,19	**1,36**	1,57	1,73	1,55	1,73
General	-	1,31	1,67	2,00	1,78	1,87	1,71
Ortho	-	1,00	1,33	1,42	1,90	1,58	1,64
Urology	-	1,25	1,17	1,50	1,47	1,43	2,13
Vascular	-	1,13	1,10	1,33	2,25	1,25	1,50

Using the instances from CHLN the number of used surgeons is higher than CHLN plan, with a variation from 7,1% in ME to 26,2% in MC.Mix, compared with CHLN plan (Table 28). These variations may be related with the actual planning at the hospital with surgeons' pre-established schedules not taken into consideration in the models. The same is valid for the low value of the CHLN plan on average number of working days per surgeon, where, in a real-life scenario, surgeons opt for having fewer days of work. As can be seen, the number of required surgeons has no direct impact on the average number of working days per surgeon, being the linear correlation between both of -0,02. Hence, it is possible to conclude that having more surgeons performing surgeons does not reduce the workload, in terms of days, for those surgeons and vice versa. ME, with one less surgeon than KKD has the worst results on the average number of working days per surgeons, together with MC.Sur (1,73 days) that has 3 more surgeons than KKD. MC.Sur, although trying to represent the real scenario at hospitals and the surgeons' perspective, does not accomplish the objective on this parameter. However, it is worth highlighting that the differences are small, with a difference of 0,37 days between best and worst result. Moreover, all models have an average in each speciality of between one and two days which means that in average all surgeons have to work two days, although with fewer hours for models with better results. In HESE (Table 29), the reduced number of surgeons per speciality, compared to CHLN, and a higher number of scheduled episodes, causes the average working days to be greater in all models. The discrepancies in the scenario of HESE are likewise higher than CHLN (difference of 38,3% between best and worst results, compared with 27,2% in CHLN). The best solution on the average number of working days per surgeon is achieved by KKD (1,88 days). MC.Sur, in this case has both the greatest number of surgeons working and the greatest number of working days per surgeon, with 48 surgeons working on average 2,6 days on that week. The fact that the gap between the best result and the second-best (26,6% from KKD to ME) is much higher than the gap between second-best and worst results (9,2% from ME to MC.Sur), alongside with KKD having the smaller values for all specialities, shows that KKD effectively minimizes the average number of working days per surgeon. Also, it is the only model with two days of workload per surgeon in average, which is a great advantage for surgeons, comparing with the other models that require surgeons to work three days on average (Table 29).

Table 29 – Surgeon utilization per speciality at HESE

	Total in WL	Scheduled				
		KKD	MC.Admin	MC.Sur	MC.Mix	ME
No. of Surgeons	58	44	40	48	45	42
General	21	16	13	18	15	13
Plastic	3	2	3	2	3	3
Stomatology	3	2	2	2	2	2
Ophthalmology	14	10	11	12	11	10
Orthopedy	6	5	5	6	5	5
OTR	7	6	4	4	7	7
Urology	4	3	2	4	2	2
Avg. No. WD per Surgeon	-	**1,88**	2,40	2,60	2,43	2,38
General	-	1,69	2,62	2,83	2,67	2,62
Plastic	-	1,00	1,00	1,00	1,00	1,00
Stomatology	-	1,00	1,00	1,00	1,00	1,00
Ophthalmology	-	2,00	2,09	2,42	2,36	2,60
Orthopedy	-	3,60	4,00	4,00	4,00	3,80
OTR	-	1,50	3,00	2,50	2,00	2,00
Urology	-	1,00	1,00	1,00	1,00	1,00

However, for surgeons, hospital administrations or SNS, as decision makers, selecting a model based only on its impact in each individual parameter is not sufficient for the decision, requiring a further analysis and holistic overview of the results. Moreover, to assess the performance in each criterion, the results are also not enough since a value function is needed. The value function enables the transformation of impacts into specific scores. For instance, regarding the average number of working days per surgeons at HESE, in Table 29, if only the relative impact is analysed, KKD has the best result, followed by, ME, MC.Admin, MC.Mix and then, MC.Sur. However, the value function can change the way the result is perceived. With a linear value function, the difference from KKD to ME is much higher than ME to MC.Admin. If, on the other hand, other non-linear value functions are utilized, a difference from MC.Admin to ME may have more influence in the decision than a difference from ME to KKD. Unfortunately, the establishment of value functions which integrates the decision model, as mentioned before, is out-of-scope in this dissertation and is presented in Section 7.2 on recommendations and future work. The following subsection concludes the results' discussion, with an overview of the results of each model regarding the KPIs and discussing the results inter-KPIs.

6.3.2 Overview and Inter-indicators Analysis

To compare the models' performance, as was done in the previous subsection, both the results using CHLN and HESE instances are used. Since no value functions are assigned to the KPIs, and to simplify the evaluation, a score of one to five was given to all models in each indicator, being one assigned to the best result – best value or the closest to the best value – and five to the worst result. Furthermore, although only two distinct instances are used, the average and the variation between them are calculated. Whereas the average is necessary to assess the performance of the models' results regarding the indicator, the variation presents the quality and consistency of the results amongst tests. The table below (Table 30) shows the ranked performance of the models for the quality group of KPIs. From the variation shown in the table, in between parentheses, it is possible to see that most results are consistent among CHLN and HESE (10 out of 16 average results present zero variation in the rank). This is true mainly for the best and worst scores, whereas more variation is seen for the second, third and fourth places in each indicator. For instance, MC.Sur has the worst score in all criteria, both for CHLN and HESE instances, and although no weights are assigned to the criteria, MC.Sur is therefore considered a dominated solution of the quality group. This result is not unexpected since this model does not aim at optimizing the OR scheduling problem but instead represent the current practice performed by the surgeons when scheduling episodes. Additionally, the model of Moosavi and Ebrahimnejad (2020) present an improvement in the ranks of all KPIs in the HESE scenario. Only with a broader set of tests, using multiple other instances, is it possible to foresee the behaviour of the model with more accuracy. The same rationale is valid for all other models.

Table 30 – Model results (ranked from 1 to 5) on quality KPIs

Indicators	Best Value		KKD	MC.Admin	MC.Sur	MC.Mix	ME
Percentage of scheduled surgeries after TMRG	HV	CHLN	2	1	5	3	4
		HESE	3	2	5	4	1
		Avg. (Var)	2,5 (1)	1,5 (1)	5 (0)	3,5 (1)	2,5 (3)
Mean of the waiting time of scheduled surgeries	HV	CHLN	3	1	5	2	4
		HESE	4	1	5	2	3
		Avg. (Var)	3,5 (1)	1 (0)	5 (0)	2 (0)	3,5 (1)
Mean of the waiting time of surgeries not scheduled	LV	CHLN	3	1	5	2	4
		HESE	4	1	5	2	3
		Avg. (Var)	3,5 (1)	1 (0)	5 (0)	2 (0)	3,5 (1)
Average no. of working days per surgeon	LV	CHLN	1	3	5	2	4
		HESE	1	3	5	4	2
		Avg. (Var)	1 (0)	3 (0)	5 (0)	3 (2)	3 (2)

The similarity of the rank between the mean of the waiting time of scheduled surgeries and the waiting time of surgeries not scheduled is also worth underlining. In fact, despite being both important for hospital administrations to visualize, they are calculated using the same properties and are therefore dependent. As mentioned in the previous section, ME presents in the percentage of scheduled surgeries after TMRG, the largest gap between CHLN and HESE results (4th and 1st place in the rank respectively).

Figure 12 presents a visualization of the average rank from Table 30 and the respective variations. As can be seen, MC.Sur is dominated by all other solutions. If analysing only the average of the solutions, ME is dominated by MC.Admin and KKD, and MC.Mix is dominated by MC.Admin, nevertheless no dominant solution exists. According to the data, MC.Admin has the best average results in the first three criteria but has a lower performance regarding the average of working days per surgeon. KKD, on the contrary has the best result on the later and a lower performance in the second and third indicator along with ME. In the percentage of scheduled surgeries after TMRG, both KKD and ME have the same average, but considering the two tests, KKD presents more consistency. Developed as a mixed version between MC.Admin and MC.Sur, MC.Mix stands as supposed, for the first three KPIs. In the last one, MC.Mix and MC.Admin have the same average of 3, even though MC.Mix shows more variation between tests. Depending on the weights assigned to each criterion and if all criteria have weights greater than zero, the best solution alternates between KKD and MC.Admin.

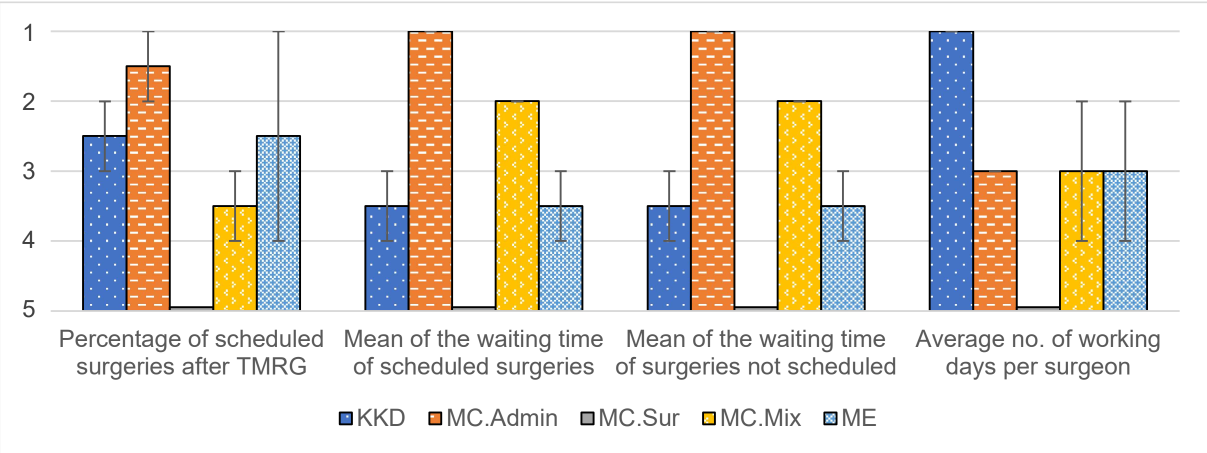

Figure 12 – Average model results (ranked from 1 to 5) and variation on quality KPIs

Regarding the production KPIs, Table 31 follows the layout of the previous table (Table 30) and reports the ranked position of the models' solutions for both CHLN and HESE instances for each criterion. The average rank and the variation between both tests are presented as well. In the first KPI – number of scheduled elective surgeries – there is almost no variation, which translates in a large consistency between both tests for all models. MC.Sur scheduled the most surgeries using both instances, followed by KKD in CHLN and HESE. MC.Admin and ME have the worst ranking, although MC.Admin performs better in CHLN and ME, once again, performs better at HESE. Concerning the amount of underutilization, there is no clear distinction on the model with the best overall performance. The top three models – MC.Admin, MC. Mix and ME – present an average score of 1,75, 2 and 2,25 with a difference smaller than 0,5 from first to third. To understand the real performance of each model, more tests are needed. KKD and MC.Admin, on the contrary, have a low performance in both tests, with an average rank of 4.5 and little variation. Regarding the amount of overutilization, although the maximum has been set to zero for all models, it is an important KPI for decision makers and therefore is presented in the table for future tests allowing overtime. The average OR occupation is a composition of underutilization and overutilization and as mentioned, for the performed tests, the overtime is equal to zero in all models. Hence, in this work there are no differences between the ranks of OR occupation rate and underutilization.

Table 31 – Model results (ranked from 1 to 5) on production KPIs

Indicators	Best Value		KKD	MC.Admin	MC.Sur	MC.Mix	ME
No. of scheduled elective surgeries	HV	CHLN	2	4	1	3	5
		HESE	2	5	1	3	4
		Avg. (Var)	2 (0)	4,5 (1)	1 (0)	3 (0)	4,5 (1)
Amount of underutilization	0	CHLN	4	2	5	1	3
		HESE	5	2,5	4	2,5	1
		Avg. (Var)	4,5 (1)	2,25 (0,5)	4,5 (1)	1,75 (1,5)	2 (2)
Amount of overutilization	0	CHLN	3	3	3	3	3
		HESE	3	3	3	3	3
		Avg. (Var)	3 (0)	3 (0)	3 (0)	3 (0)	3 (0)
Average OR occupation	100%	CHLN	4	2	5	1	3
		HESE	5	2,5	4	2,5	1
		Avg. (Var)	4,5 (1)	2,25 (0,5)	4,5 (1)	1,75 (1,5)	2 (2)

Through Figure 13, presenting the production KPIs, it is possible to denote that no solution is dominant or is dominated by all other, as was the case of MC.Sur on the quality criteria (Figure 12). In the figure, KKD and MC.Sur, the best results on the number of scheduled elective surgeries, are shown to be the models with the lowest performance regarding the utilization of the OR (average OR occupation and underutilization). Although MC.Mix stands in between the low score of MC.Admin and the high score of MC.Sur in the first production KPI, the findings of MC.Mix have a better score than the latter two in underutilization and therefore OR occupation rate. Both MC.Admin and ME are dominated by MC.Mix, and KKD is dominated by MC.Sur. This implies that depending on the weight of each criteria, the best solution on the production group alternates between MC.Mix and MC.Sur.

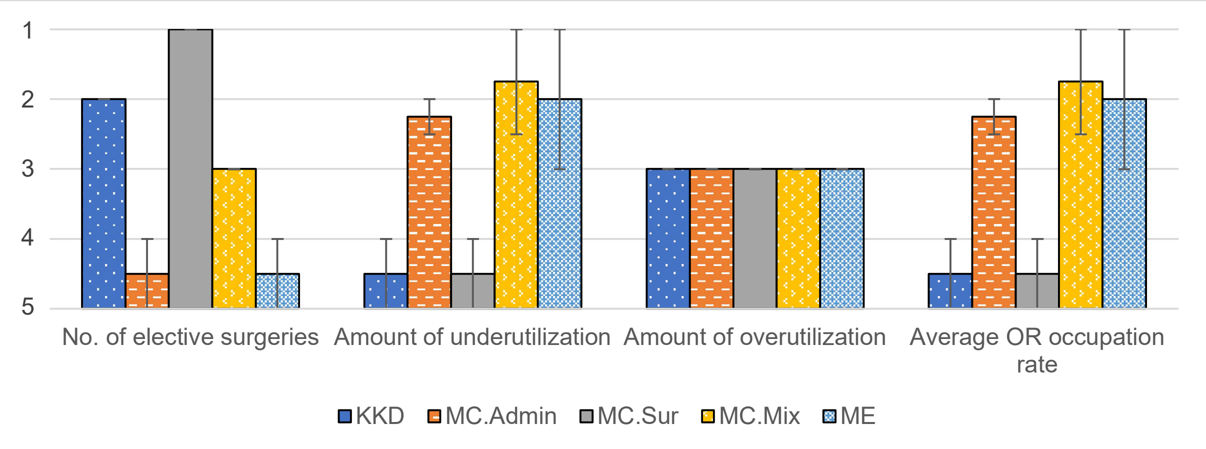

Figure 13 – Average model results (ranked from 1 to 5) and variation on production KPIs

Finally, concerning the last group of KPIs – productivity – Table 32 portrays the ranked solutions from each model using CHLN and HESE instances. Following the same arrangement, for each indicator, the average rank and the variation between tests is presented. As the MSS was given a priori, the number of blocks (43 in CHLN and 29 in HESE) and specialities (4 in CHLN and 7 in HESE) is constant amongst all models. This particularity leads to results proportional only to the number of scheduled surgeries (discussed previously) in the indicators of average number of surgeries per block and per speciality. If a decision model is built, based on the indicators discussed in this work, attention is required since these two indicators are a mirrored representation on the number of scheduled surgeries. Nevertheless, the information portrayed by the indicators is useful for the SNS and hospital administrations mainly to compare with the current situation or homologous periods from other years. With respect to the number of surgeries per surgeons, this indicator is a composite of the number of scheduled surgeries and also the number of required surgeons. Although aiming at reducing the number of working days per surgeon, KKD has ranked first in both tests, suggesting a good optimization of the surgeons. MC.Mix has the lowest performance both in CHLN and HESE experiments.

Table 32 – Model results (ranked from 1 to 5) on productivity KPIs

Indicators	Best Value		KKD	MC.Admin	MC.Sur	MC.Mix	ME
Average no. of surgeries per block	HV	CHLN	2	4	1	3	5
		HESE	2	5	1	3	4
		Avg. (Var)	2 (0)	4,5 (1)	1 (0)	3 (0)	4,5 (1)
Average no. of surgeries per speciality	HV	CHLN	2	4	1	3	5
		HESE	2	5	1	3	4
		Avg. (Var)	2 (0)	4,5 (1)	1 (0)	3 (0)	4,5 (1)
Average no. of surgeries per surgeon	HV	CHLN	1	4	2	5	3
		HESE	1	2	3	5	4
		Avg. (Var)	1 (0)	3 (2)	2,5 (1)	5 (0)	3,5 (1)

In Figure 14 it is noticeable that the first two KPIs – average number of surgeries per block and per speciality – are equal in terms of ranking with MC.Sur in first, KKD in second and MC.Mix in third with no variations between tests. In the third KPI – average number of surgeries per surgeon – KKD has the best results, with a clear margin from the other models. When analysing the overall results in the productivity group, all three averaged solutions of MC.Admin, MC.Mix and ME are dominated by MC.Sur and KKD, mainly due to the high number of scheduled surgeries achieved by MC.Sur and KKD and the efficiency in the use of surgeons by KKD. No dominance exists between KKD and MC.Sur, being the best one dependent on the weights given to the criteria.

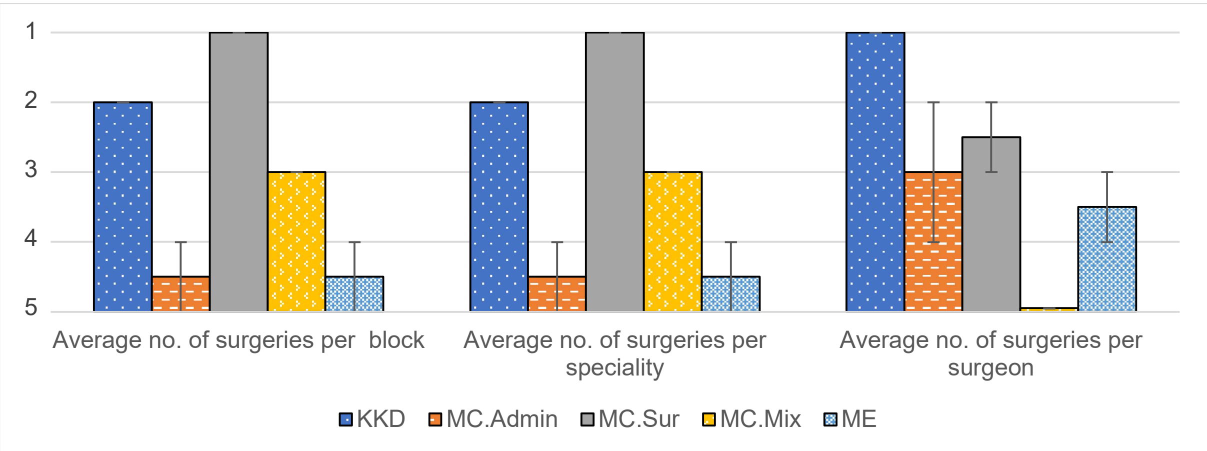

Figure 14 – Average model results (ranked from 1 to 5) and variation on productivity KPIs

In a general analysis, overviewing together all indicator groups, it is visible that the performance of each model also varies according to the groups. The administration's version of Marques and Captivo (2020), MC.Admin, has a clear focus on equity in access, with a concern for providing timely care and scheduling the patients with larger waiting times. This focus is reflected in the high results in the quality group of KPIs, although probably at the cost of the performance in production and productivity related indicators as can be seen in Figure 15. MC.Sur, contrarily to MC.Admin, has the objective of mimicking the surgeons' behaviour, which is more focused on production and not in the waiting time of the patients, presenting high performance on the number of scheduled surgeries and productivity but low performance on quality and other KPIs. The mixed version, MC.Mix as expected, is a compromise between the former two models, but distinguishes from both on the KPIs of underutilization and OR occupation rate. More computational experiments with other instances and allowing for overtime are necessary to establish a reliable pattern. KKD has a clear advantage when analysing the surgeons as stakeholders, since not only it accomplishes the best surgeon performance on productivity but also aims at the minimization of the number of working days, allowing more time for surgeons to perform duties in other facilities. At last, the model of Moosavi and Ebrahimnejad (2020) has a relative average performance on the selected matrix, not achieving any first position on the criteria. The lower performance can be the consequence of being a model built towards a broader spectrum of objectives and parameters, as discussed on Section 4.5, which is adapted for this work, compromising the performance of the results when compared to the other models which focus only on the studied objectives. Nevertheless, amongst all groups of KPIs, no model's solution is dominated or dominates any other, hence supporting that all models are valid and only the establishment of weights for each criterion through a decision model can determine a hierarchy between the models.

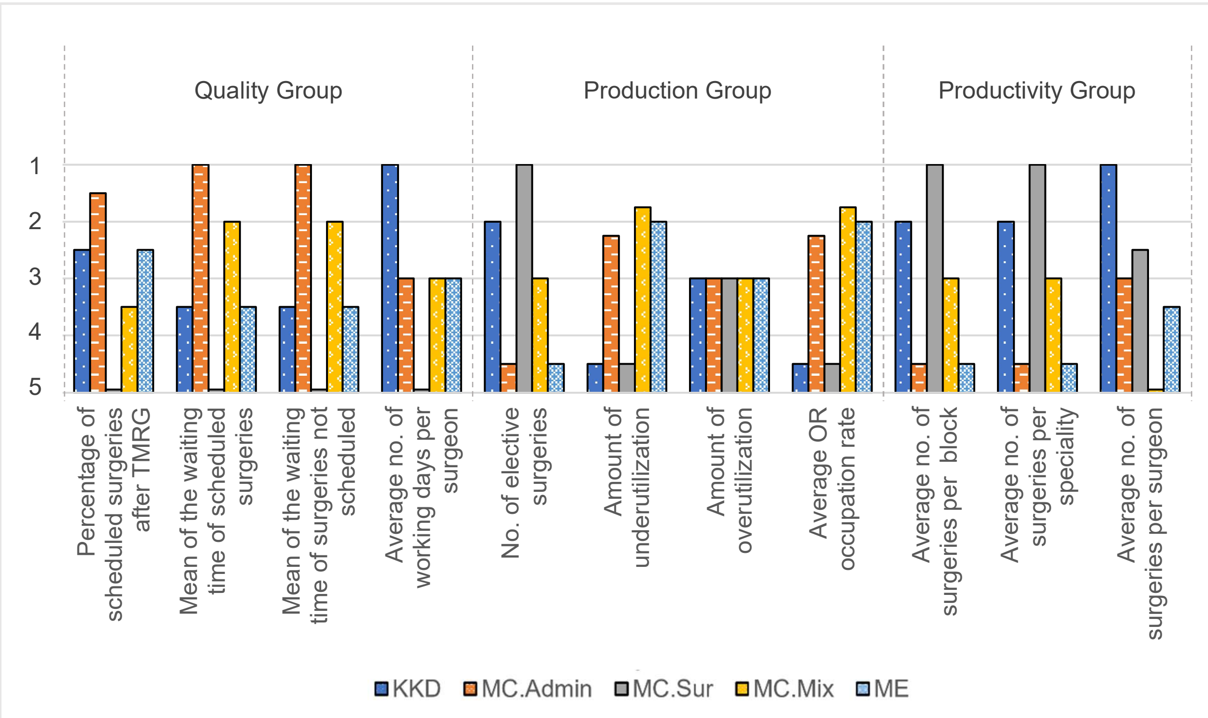

Figure 15 – Overall model results (ranked from 1 to 5) on the selected KPIs

7 Conclusions and Future Work

The health care services are complex systems that require coexistence and interaction of multiple stakeholders. In OTs, the efficient scheduling of patients is essential to promote both equity and timely access to patients and a cost-effective utilization of resources. Although seen many times as two disjoint or mutually exclusive factors, the surgical production and stakeholders' satisfaction can be balanced, and trade-offs can be achieved to develop social and economically sustainable solutions. In this dissertation, the surgery planning and scheduling procedure in SNS is studied. Throughout the last years, the surgical demand and production has risen. In 2018 there were 594 978 surgeries performed in SNS for a total of 706 103 patients awaiting surgery, which portrays a ratio of 1.18 between demand and supply (20% more demand than supply). The optimization of these services is therefore essential, not only to employ the given budget as efficiently as possible but also to answer to the high surgery demand observed. To understand the processes in real scenarios, this work focuses on the case studies of CHLN and HESE, two SNS hospitals from two different regions and with distinct volumes of production. The case studies revealed that, although regulations on patient scheduling exist, most scheduling is performed by surgeons empirically, without following the specific guidelines. In 2015 a study to evaluate the OT's situation in Portugal (Penedo et al. 2015) was developed, which showed that there was space for improvement, although thus far no follow-up study has been carried out.

According to the SNS guidelines, patients must be scheduled in order of priority, starting with the highest priority episodes. For surgeries with the same priority, a FIFO sequencing rule is to be used, letting patients with greater wating times to be scheduled first. However, as mentioned, hospitals do not follow the standard procedure and to corroborate, when analysing the CHLN plan, it is possible to see that patients from priority two and one have been scheduled whilst priority three patients were still on the waiting list. To understand how the standardization of the operational level of surgery planning and scheduling across the SNS can arise, a review of literature on the subject was performed. Through the extensive literature review it is possible to understand that, even though there are several papers addressing the subject, there are distinctive approaches and instances which produce incomparable results, making it difficult for SNS or hospitals' administrations to select a single scheduling model. This dissertation has the objective of establishing a general matrix of KPIs that allow the measurement of the surgical production and the satisfaction of patients, surgeons and the hospitals' administration as OT stakeholders through quantitative criteria. Amongst the analysed literature, models from three papers have been selected (Kamran et al. 2018; Marques and Captivo 2017; Moosavi and Ebrahimnejad 2020) for their coverage on different stakeholders, namely patients, surgeons and hospital administrations. Although Kamran et al. (2018) and Moosavi and Ebrahimnejad (2020) present only one model in their papers, Marques and Captivo (2017) present three different versions, one from the administration's perspective, one for the surgeon's perspective and a mixed version. All five models are tested using large sized instances for a specific week, from CHLN (3 033 patients and 148 surgeons from four specialities) and HESE (2 437 patients and 58 surgeons from 7 specialities). While Kamran et al. (2018) obtains optimal solutions in both tests, all other models are able only to obtain feasible solutions in the settled time of 10 minutes, although with gaps smaller than 0,60%, concluding that all solutions are close to optimality and, thus, the comparisons established are fair. The quality of the solutions according to the defined matrix of KPIs, however, varies between the different models and the criteria themselves. From the patients' perspective, when compared to the real scheduling plan from CHLN, all models are able to schedule more patients and particularly those with waiting times higher than TMRG, with the exception of the surgeons' version of Marques and Captivo (2017), MC.Sur, that only schedules patients within the TMRG. The distinction between MC.Sur and the remaining models is clear in most indicators since the objective of this version is to mimic the surgeons' behaviour and not to optimize the process in the same way as the others. For that reason, despite the good performance in terms of number of scheduled patients (best surgical production), it is recommended that MC.Sur is not included in the group of models that can be adapted by SNS to schedule surgeries.

Regarding the best results related to tardy surgeries, the administration version of Marques and Captivo (2017), MC.Admin, has a clear focus on selecting patients with the greatest waiting time, but the findings of Kamran et al. (2018) – KKD – and Moosavi and Ebrahimnejad (2020) – ME – show a higher number of tardy patients selected, but with a lower average of days out of TMRG. The mixed version of Marques and Captivo (2017), MC.Mix, as the name suggests, is between MC.Admin and MC.Sur, compromising the performance of MC.Admin in these indicators. In some indicators, a variation between the findings of the computational experiments using CHLN and HESE is observed. For example, ME shows a greater variation between tests, with a percentage of 44,57% tardy patients scheduled in CHLN test and 93,28% in HESE. These variations show that testing only two instances may compromise the accuracy of the findings from a statistical point-of-view. When considering the surgeons as one of the main stakeholders in the surgery scheduling process, an interesting particularity of KKD is the aim of minimizing the number of surgeons' working days. Being the only model that attempts to do so, it is, as expected, the model with the best performance in both tests, with less than two days of work in average per surgeon. Additionally, KKD is the model that presents solutions with the best performance on the surgeons' productivity on both tests, whereas the other model solutions vary depending on the instances used. Variations are more prominent on the underutilization KPI, where no model achieved a stable score between tests. Regarding the effective number of scheduled surgeries, MC.Sur and KKD present the best performance. The lower performance of ME findings in all criteria can be the consequence of being a model developed to include also up- and downstream resources and overtime, which is adapted for this work, compromising the performance of the results when compared to the other models that focus only on the studied objectives.

Through this work, it also possible to denote that to select a scheduling model, trade-offs between KPIs need to occur. Therefore, as no dominant solution has been found amongst the models, and to complement the work performed in this dissertation, a decision model is essential. Not only will the model establish the value functions for each indicator, which are needed to accurately understand the differences between the models' findings in each KPI, but also to determine the weight of each KPI. To properly build this decision model, decision makers have to be defined, although, to ensure feasibility and higher hospital implementation of the scheduling model, it is recommended that they are from a centralized institution. The decision maker can in this case be the responsible for SIGIC program in

SNS, the ACSS, or if it is proved to be impractical, the hospital administrations, considering that all hospital administrations under SNS pursue the same objectives and are therefore deemed as equals.

Moreover, as mentioned before, to improve the accuracy and quality of the solutions, further testing with instances from other hospitals or different years is needed to ensure that the variations amongst models' findings are reduced and statistical stability is achieved. Also, as this works demonstrates, the comparison between the findings and actual hospital plans are helpful to understand the differences and improvements in the studied scenarios. Finally, it is important to denote that this work was solely studying the operational level of OR planning and scheduling, in a perioperative approach, with no inclusion of both up- and downstream resources such as ICU and ward beds. Although most research pointed that if those resources are abundant, no bottlenecks are to occur, their scarcity often changes the overall scenario. In cases where the surgical production optimization is more evident, the availability of up- and downstream resources can change and must be accounted. Similarly, parallel divisions, for instance, nurses, anaesthesiologists and other required staff are not included. When considering the feasibility of the optimal solutions of the models in real scenarios it is especially important to consider the anaesthesiologists since different studies (Ordem dos Médicos 2017; Penedo et al. 2015) describe them as a limiting factor in SNS hospitals surgical production. Since the papers and models to be compared in this dissertation's benchmark are chosen in the light of what has been studied, if these new external factors are to be included, the criteria to select which papers to partake in the test must also be reviewed.

The extension of this work beyond the operational level of OR planning and scheduling to tactical and strategic levels of planning through a bottom-up analysis has also potential benefits. To give an example, as mentioned in the work, the fact that surgeries with lower waiting times are being scheduled whilst there are episodes with higher wating times in the list and even episodes out of due date, should alert to the possibility that some metrics conceived in the payment contracts between hospitals and each ARS are not suitable for the sustainable functioning of the OTs. Observing only the quality of the attained solutions to each stakeholder perspective without examining the metrics used in the payment contracts which hospitals are required to fulfil can lead to economically unviable proposals. The examination of the metrics used in the contracts and the improvement of this dissertation based on the mentioned above is beneficial for future work.

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Appendix A. HSM and HESE's Operating Theatre Plants

Figure A1 – COT’s OT plant from HSM (adapted from Patrão, 2018)

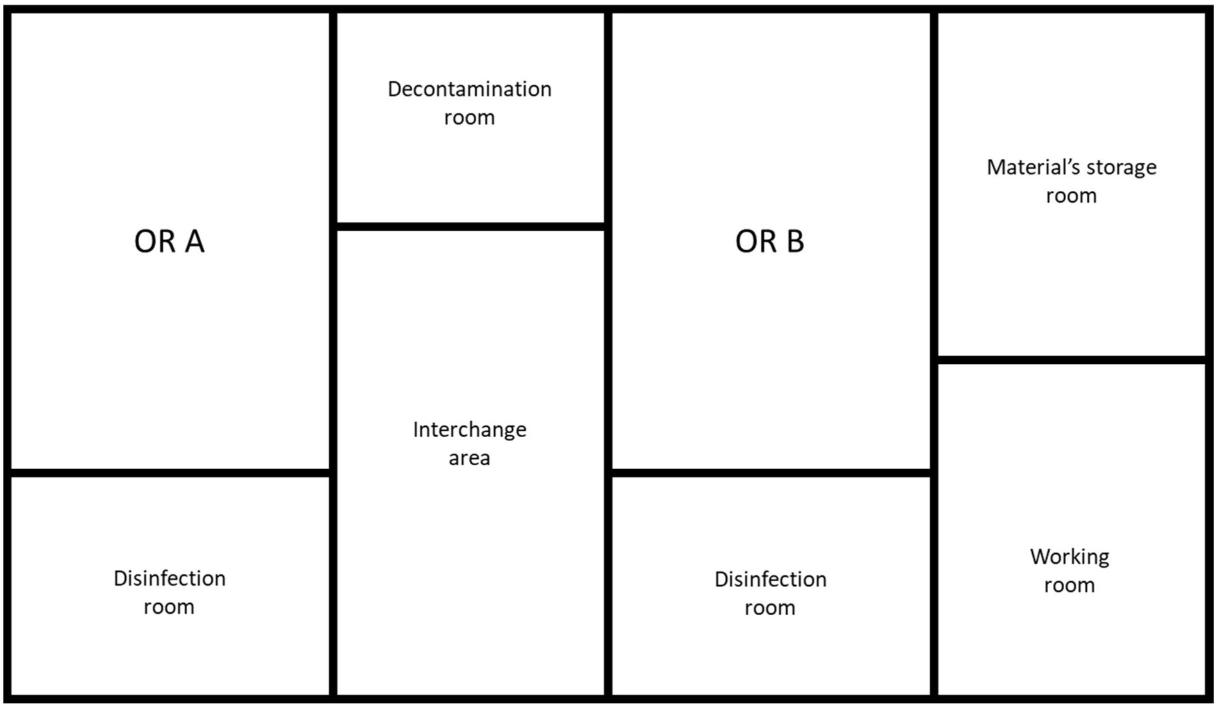
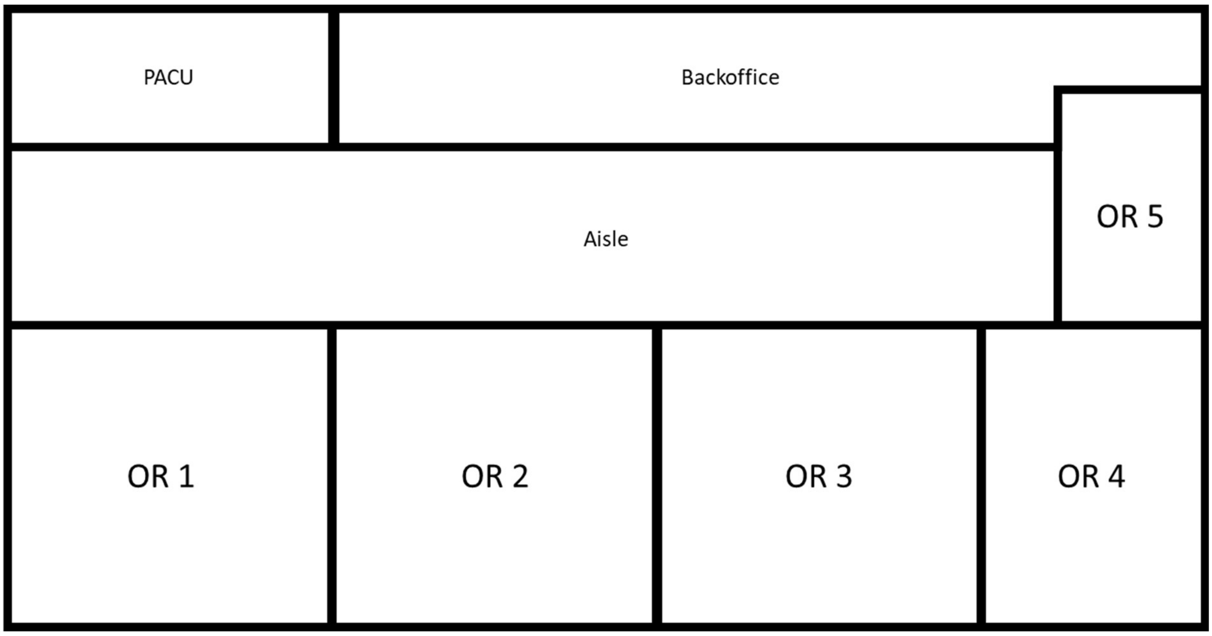


Figure A2 – COT’s plant from HESE (adapted from Lubomirska, 2018)



Appendix B. Operating Theatre Performance Indicators

Table B1 – OT performance indicators (adapted from Penedo et al., 2015)

Group	Indicators	Value of reference	CHLN		HESE	
			2014	2018[i]	2015	2018
Quality	Percentage of performed surgeries after TMRG	< 10%	N/A	36,2%	N/A	29,3%
	Median of the waiting time	< 90 days	120 days	132 days	99 days	84 days
Production	No. of elective surgeries	-	29 779	29 461	13 491	14 590
	No. of non-elective surgeries	-	5 181	6 161	1 599	1 700
	Average OR utilization time		121 min	N/A	66 min	N/A
	Average OR setup time	20 min per surgery	14 min	N/A	19 min	N/A
	No. of standardized surgeries[ii]	-	25 875	20 956	9 894	7 838
	Percentage of outpatient surgeries	-	45%	62%	58%	67%
	Average cost of OR per hour	-	439€	N/A	940€	N/A
Productivity	No. of standard surgeries per adjusted standard surgeon[iii]	2,6 per week (equivalent to 5,2 performed surgeries)	2,5	N/A	2,2	N/A
	No. of standard surgeries per adjusted standard anaesthesiologist[iv]	8,75 per week	8,5	N/A	13,9	N/A
	No. of standard surgeries per OR	30 per week	20,2	N/A	37,5	N/A

[i] Values from 2018 were extracted from (Ministério da Saúde 2019) considering 40 working hours per week.
[ii] Number of normal elective surgeries plus additional surgeries adjusted to the complexity of each surgery (average relative weight of surgeries)
[iii] Number of surgeons with 35 working hours per week, plus hours used for additional production. The hours of the internship surgeons are considered with a factor of 0,5. Are considered 44 weeks of work in a year. Hours of additional production are accounted having in consideration the number of additional production surgeries with a standard surgery length with two surgeons.
[iv] Number of anaesthesiologists with 35 working hours per week, plus hours used for additional production. Are considered 44 weeks of work in a year. Hours of additional production are accounted having in consideration the number of additional production surgeries with a standard surgery length and a factor of 1,5.

Appendix C. Literature Review Summary

Table C1 – Summary of the literature review

	Operational Decision Level			Scheduling Strategy				Patient Characteristics							Problem Features									Objective Function
								Type of Admission				Length of stay			Uncertainty					Vertical Integration				
	Advance	Allocation	Both	Block	Open	Modified	N/A	Elective	Emergency	Urgency	N/A	In	Out	N/A	Duration	LOS	Arrival	Emergencies	Resources	PHU	PACU	Wards	ICU	
(Abdeljaouad et al. 2014)		✓			✓			✓						✓										1
(Abedini et al. 2016)		✓			✓			✓						✓										2
(Addis et al. 2014)	✓			✓				✓						✓	✓									3;4;5
(Addis et al. 2016)			✓	✓				✓						✓	✓			✓						3;5
(Agnetis et al. 2014)	✓			✓				✓						✓										3
(Ansarifar et al. 2018)			✓				✓	✓						✓	✓					✓		✓		6
(Aringhieri et al. 2015a)	✓			✓				✓																3
(Aringhieri et al. 2015b)	✓			✓				✓														✓		7
(Astaraky and Patrick 2015)	✓						✓	✓	✓					✓			✓					✓		3;7;8
(Augusto et al. 2010)		✓			✓			✓						✓								✓		1
(Azari-Rad et al. 2014)		✓		✓				✓	✓			✓	✓					✓	✓		✓	✓	✓	10
(Barz and Rajaram 2015)	✓						✓	✓	✓					✓			✓	✓	✓			✓	✓	11
(Batun et al. 2011)			✓		✓			✓						✓	✓									2;8;12
(Berg and Denton 2017)		✓					✓				✓		✓		✓		✓							2
(Bilgin et al. 2012)		✓					✓	✓						✓								✓		13
(Bouguerra et al. 2015)		✓			✓			✓						✓										6;11
(Bruni et al. 2015)			✓	✓				✓	✓					✓	✓			✓						3;11
(Cardoen et al. 2009a)		✓		✓				✓				✓									✓			3;7;13
(Cardoen et al. 2009b)		✓		✓				✓				✓									✓			3;7;13
(Castro and Marques 2015)		✓			✓			✓		✓		✓	✓											6
(Castro and Petrovic 2012)		✓		✓				✓	✓	✓				✓										5
(Ceschia and Schaerf 2016)	✓			✓				✓		✓				✓	✓	✓		✓				✓		7
(Chaabane et al. 2008)	✓			✓	✓			✓						✓								✓		4
(Choi and Wilhelm 2012)			✓	✓				✓					✓		✓									3;12
(Dekhici and Belkadi 2010)		✓					✓	✓						✓								✓		1
(Denton et al. 2007)			✓	✓				✓				✓	✓		✓									3;5;12
(Díaz-López et al. 2018)			✓		✓			✓						✓	✓									6
(Dios et al. 2015)			✓		✓			✓						✓	✓									3;13
(Does et al. 2009)		✓					✓	✓						✓										12;99
(Doulabi et al. 2016)			✓		✓			✓						✓										6
(Duma and Aringhieri 2019)			✓				✓	✓	✓	✓				✓	✓			✓						6;10
(Durán, Rey, and Wolff 2017)			✓	✓							✓			✓										3;8;13
(Erdogan and Denton 2013)		✓					✓				✓			✓	✓		✓					✓		3;8
(Fei et al. 2009)	✓				✓			✓						✓										6;8
(Fei et al. 2010)			✓	✓		✓		✓						✓								✓		8;9
(Ferreira 2017)	✓			✓				✓		✓		✓	✓											3
(Guda et al. 2016)		✓					✓	✓				✓	✓		✓		✓							5

Objective functions – **1.** Minimize the makespan; **2.** Minimize the no. of open ORs; **3.** Minimize the waiting time; **4.** Minimize the no. of unscheduled patients; **5.** Minimize the tardiness of patients; **6.** Maximize the OR utilization; **7.** Level post-operative resources; **8.** Minimize overtime/overutilization; **9.** Minimize undertime/underutilization; **10.** Minimize the no. of surgery cancellations; **11.** Maximize profits; **12.** Minimize idle time; **13.** Maximize patient preferences; **14.** Maximize staff affinity; **99.** Other objectives

	Operational Decision Level			Scheduling Strategy				Patient Characteristics							Problem Features								Objective Function
								Type of Admission				Length of stay			Uncertainty					Vertical Integration				
	Advance	Allocation	Both	Block	Open	Modified	N/A	Elective	Emergency	Urgency	N/A	In	Out	N/A	Duration	LOS	Arrival	Emergencies	Resources	PHU	PACU	Wards	ICU	
(Guido and Conforti 2017)	✓			✓				✓						✓										3;4;8;9
(Guo et al. 2016)			✓	✓				✓						✓										2
(Hamid et al. 2017)		✓					✓	✓						✓								✓		8;9
(Hamid et al. 2019)		✓		✓				✓				✓			✓	✓	✓				✓		✓	3;5
(Herring and Herrmann 2012)		✓					✓	✓						✓			✓							9;10
(Huang et al. 2018)			✓				✓				✓			✓	✓				✓			✓		4;12
(Jebali and Diabat 2015)	✓						✓	✓				✓			✓	✓						✓	✓	3;8;9
(Jebali et al. 2006)			✓				✓							✓						✓	✓		✓	3;8;9
(Kamran et al. 2018)	✓					✓		✓	✓	✓		✓			✓	✓								3;4;5;8;99
(Kamran et al. 2019)			✓			✓		✓	✓					✓	✓			✓						3;4;5;8;99
(Khaniyev et al. 2020)		✓		✓				✓						✓	✓									3;8;12
(Kong et al. 2013)		✓					✓	✓					✓		✓									3
(Kroer et al. 2018)		✓			✓			✓	✓					✓	✓			✓						2;8
(Lamiri et al. 2007)	✓			✓		✓		✓	✓					✓	✓			✓						3;8
(Lamiri, Augusto, et al. 2008)		✓					✓	✓						✓							✓			5
(Lamiri, Xie, Dolgui, et al. 2008)	✓			✓				✓	✓					✓	✓			✓						3;8
(Lamiri, Xie, and Zhang 2008)	✓			✓		✓		✓	✓					✓				✓						3;8
(Landa et al. 2016)			✓	✓				✓						✓	✓							✓		6
(Latorre-Núñez et al. 2016)		✓					✓	✓	✓			✓	✓		✓			✓			✓		✓	1
(Lee and Yih 2014)		✓		✓				✓						✓	✓				✓		✓			1
(Li, Gupta, and Potthoff 2016)		✓		✓				✓						✓										99
(Liang et al. 2015)		✓					✓	✓						✓	✓									3;4
(Liu et al. 2011)		✓			✓						✓			✓										8;9
(Liu et al. 2019)			✓		✓			✓	✓					✓			✓	✓				✓	✓	11
(Ma and Demeulemeester 2013)			✓	✓				✓				✓			✓	✓	✓					✓		7;11
(Marcon and Dexter 2006)		✓					✓	✓		✓				✓	✓	✓					✓			7;8
(Marques and Captivo 2015)			✓	✓				✓		✓		✓	✓											4;6
(Marques and Captivo 2017)	✓			✓				✓		✓		✓	✓		✓									3;4;5
(Marques et al. 2012a)	✓				✓			✓		✓		✓	✓											6
(Marques et al. 2012b)	✓				✓			✓		✓		✓	✓											6
(Marques et al. 2014)			✓		✓			✓		✓		✓	✓											4;6
(Marques et al. 2015)			✓		✓			✓		✓		✓	✓											4;6
(Meskens et al. 2013)		✓		✓				✓				✓	✓										✓	1;8;14
(M'Hallah and Al-Roomi 2014)			✓	✓				✓						✓	✓						✓	✓		4;8;9
(Min and Yih 2010a)	✓				✓			✓	✓					✓	✓		✓							8;10
(Min and Yih 2010b)	✓			✓				✓						✓	✓	✓							✓	3;8
(Molina-Pariente et al. 2009)	✓			✓	✓			✓				✓												13
(Molina-Pariente et al. 2015)			✓	✓	✓			✓						✓	✓				✓					4;5;12
(Moosavi and Ebrahimnejad 2018)			✓	✓				✓	✓					✓	✓	✓		✓		✓			✓	3;4;8;12;99
(Moosavi and Ebrahimnejad 2020)	✓			✓				✓	✓					✓	✓	✓		✓					✓	3;7;8;12

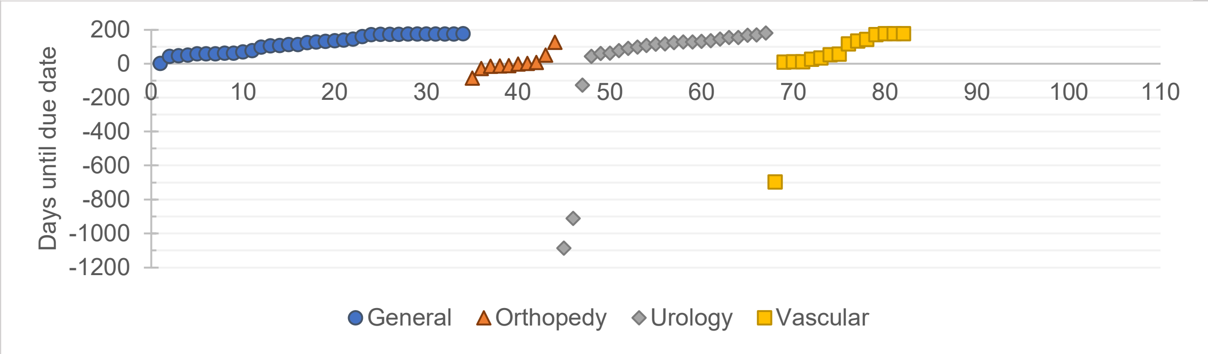
Objective functions – **1.** Minimize the makespan; **2.** Minimize the no. of open ORs; **3.** Minimize the waiting time; **4.** Minimize the no. of unscheduled patients; **5.** Minimize the tardiness of patients; **6.** Maximize the OR utilization; **7.** Level post-operative resources; **8.** Minimize overtime/overutilization; **9.** Minimize undertime/underutilization; **10.** Minimize the no. of surgery cancellations; **11.** Maximize profits; **12.** Minimize idle time; **13.** Maximize patient preferences; **14.** Maximize staff affinity; **99.** Other objectives

	Operational Decision Level			Scheduling Strategy				Patient Characteristics							Problem Features									Objective Function
								Type of Admission				Length of stay			Uncertainty					Vertical Integration				
	Advance	Allocation	Both	Block	Open	Modified	N/A	Elective	Emergency	Urgency	N/A	In	Out	N/A	Duration	LOS	Arrival	Emergencies	Resources	PHU	PACU	Wards	ICU	
(Niu et al. 2013)		✓					✓				✓	✓			✓	✓	✓				✓			4;6
(Noorizadegan and Seifi 2018)			✓	✓				✓						✓	✓									2;12
(Ozen et al. 2016)		✓					✓	✓				✓												6;11
(Perdomo, Augusto, and Xie 2008)		✓			✓			✓				✓										✓		5
(Pham and Klinkert 2008)			✓			✓		✓		✓		✓	✓								✓		✓	1;3
(Pulido Martínez et al. 2014)		✓					✓	✓						✓	✓									3;8;12
(Rachuba and Werners 2017)	✓			✓				✓	✓					✓	✓			✓						3;4;8
(Rath et al. 2017)		✓						✓				✓	✓		✓									2;8; 99
(Razmi et al. 2015)	✓			✓				✓	✓					✓				✓	✓					3;8
(Riise and Burke 2011)			✓	✓				✓						✓										3;8;13
(Riise, Mannino, and Burke 2016)			✓	✓				✓						✓								✓		1
(Roland et al. 2007)			✓				✓				✓			✓										2;8
(Roshanaei et al. 2017a)		✓			✓			✓						✓										2;8;99
(Roshanaei et al. 2017b)	✓			✓				✓						✓										2;3;4
(Roshanaei et al. 2020)			✓		✓			✓						✓	✓									4;6
(Saadouli et al. 2014)			✓		✓			✓						✓	✓									1;99
(Saadouli et al. 2015)	✓				✓			✓						✓	✓	✓			✓			✓		1;3
(Schmid and Doerner 2014)		✓			✓						✓			✓						✓				3;12
(Shylo et al. 2013)	✓			✓				✓						✓	✓									6
(Silva et al. 2015)			✓	✓				✓						✓	✓								✓	6
(Souki 2011)		✓					✓				✓			✓	✓	✓					✓			1
(Su et al. 2011)		✓			✓						✓			✓										1;12
(Tan et al. 2011)	✓			✓				✓						✓								✓		99
(Testi and Tànfani 2009)	✓			✓				✓				✓										✓	✓	3;13
(Testi et al. 2007)		✓		✓				✓				✓			✓	✓	✓	✓				✓		4;99
(Vali-Siar et al. 2018)			✓		✓		✓	✓						✓	✓	✓					✓	✓	✓	5;8;12
(van Essen et al. 2012)		✓			✓		✓		✓			✓			✓			✓						99
(Van Huele and Vanhoucke 2014)			✓		✓			✓						✓							✓			8
(Vancroonenburg et al. 2015)			✓		✓			✓						✓							✓			4;99
(Vijayakumar et al. 2013)			✓	✓				✓						✓										4
(Wang et al. 2015)			✓		✓			✓						✓								✓		3;13
(Weiss 2014)	✓			✓				✓	✓	✓				✓	✓									2
(Wullink et al. 2007)		✓		✓					✓					✓	✓			✓						3;6;8
(Xiang et al. 2015a)		✓			✓			✓				✓	✓							✓	✓			1
(Xiang et al. 2015b)		✓			✓			✓						✓	✓	✓				✓	✓			1
(Zhang and Xie 2015)		✓			✓						✓			✓	✓									8;12
(Zhang et al. 2014)		✓				✓		✓						✓	✓		✓							3;8;12
(Zhang et al. 2019)	✓				✓			✓						✓	✓	✓	✓						✓	2;8;10;99
(Zhao and Li 2014)		✓			✓			✓					✓											2;8
(Zhu 2011)		✓					✓	✓				✓			✓									2;8;9

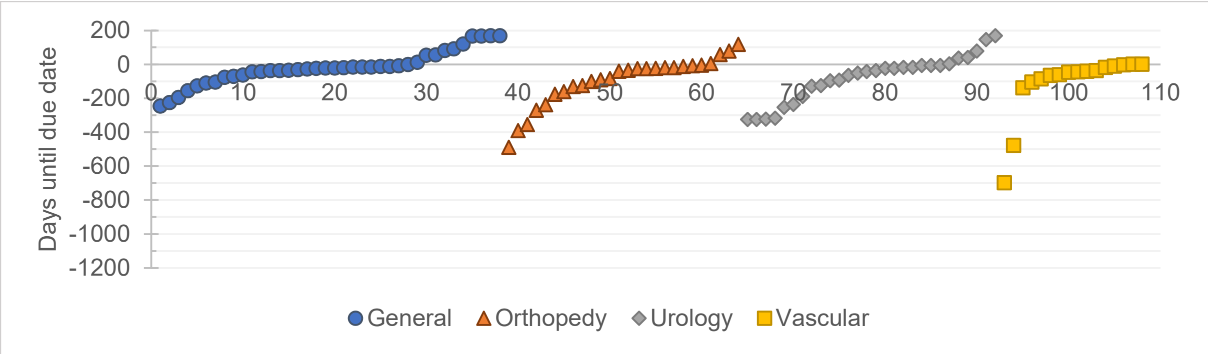
Objective functions – **1.** Minimize the makespan; **2.** Minimize the no. of open ORs; **3.** Minimize the waiting time; **4.** Minimize the no. of unscheduled patients; **5.** Minimize the tardiness of patients; **6.** Maximize the OR utilization; **7.** Level post-operative resources; **8.** Minimize overtime/overutilization; **9.** Minimize undertime/underutilization; **10.** Minimize the no. of surgery cancellations; **11.** Maximize profits; **12.** Minimize idle time; **13.** Maximize patient preferences; **14.** Maximize staff affinity; **99.** Other objectives

Appendix D. Distribution of Scheduled Episodes

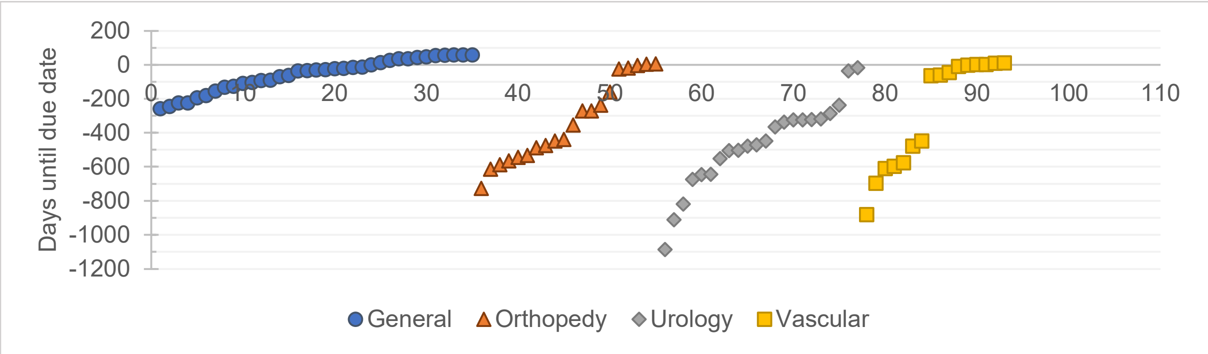
Figure D1 – Scheduled patients according to the number of days until due date in CHLN



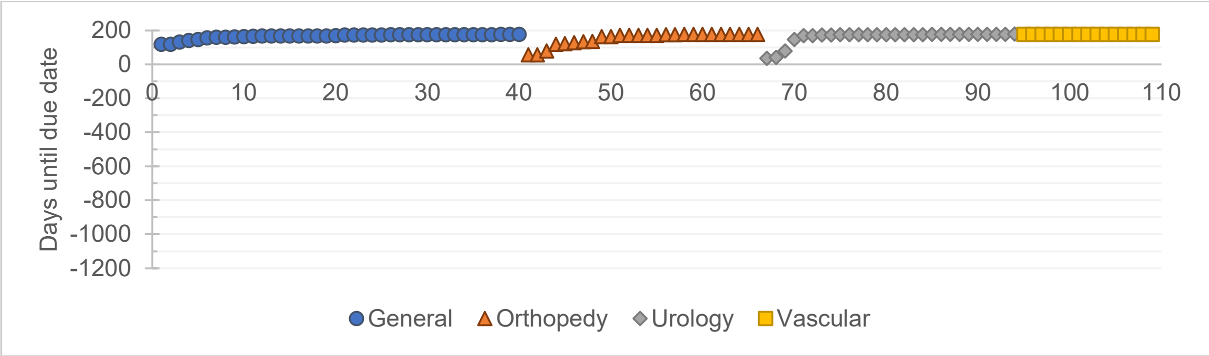
a) CHLN surgical plan



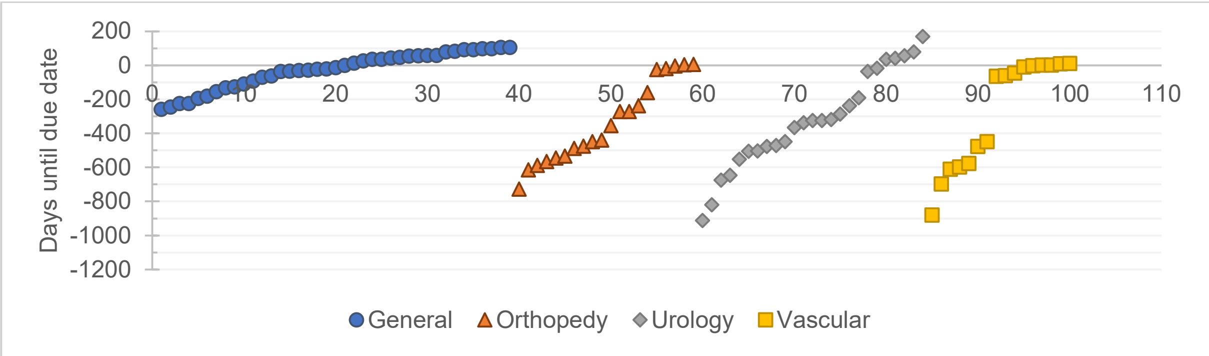
b) Kamran et al. (2018)



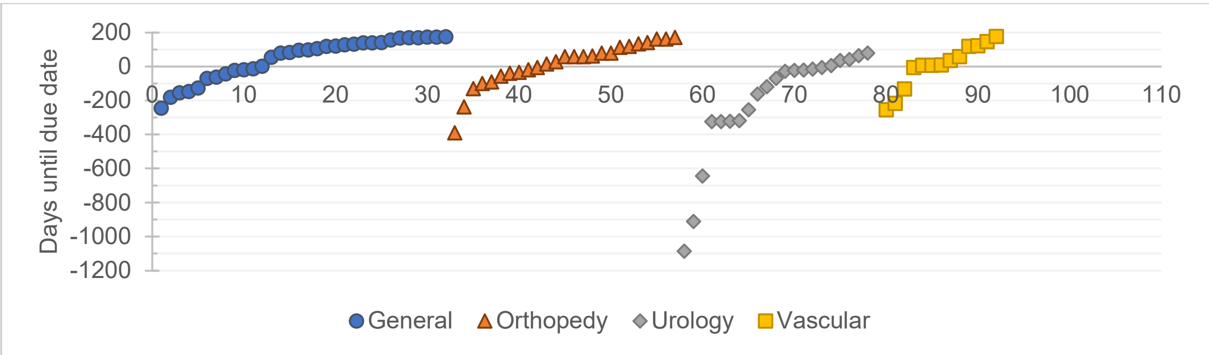
c) Marques and Captivo (2017) – Administration version



d) Marques and Captivo (2017) – Surgeons' version

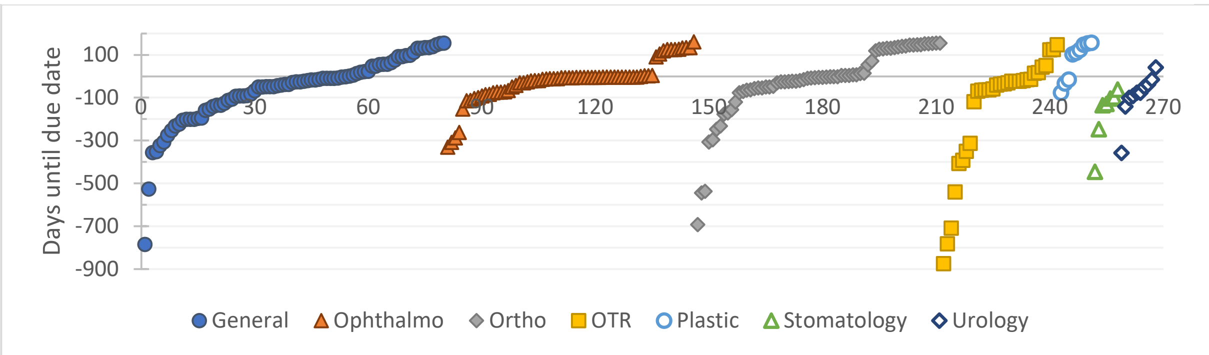


e) Marques and Captivo (2017) – Mixed version

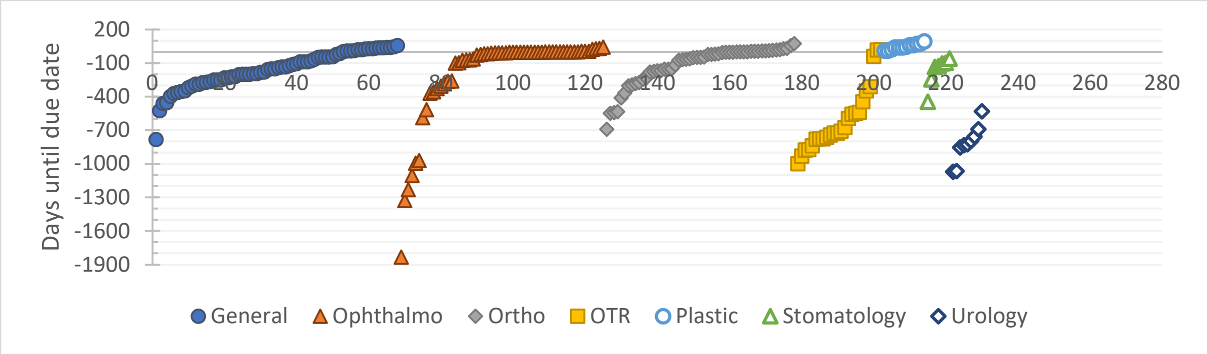


f) Moosavi and Ebrahimnejad (2020)

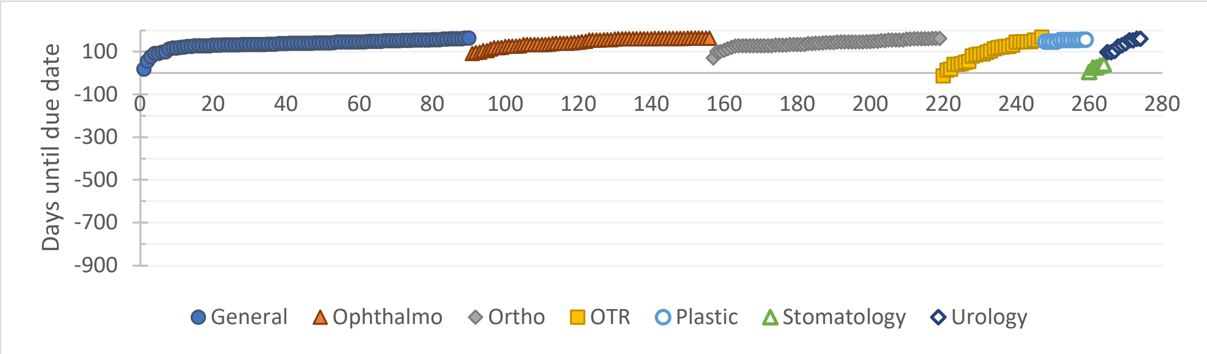
Figure D2 – Scheduled patients according to the number of days until due date in HESE



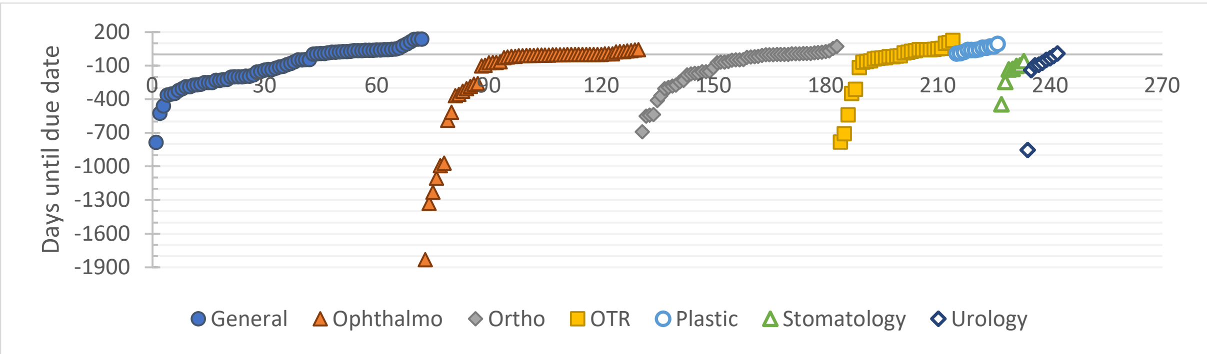
a) Kamran et al. (2018)



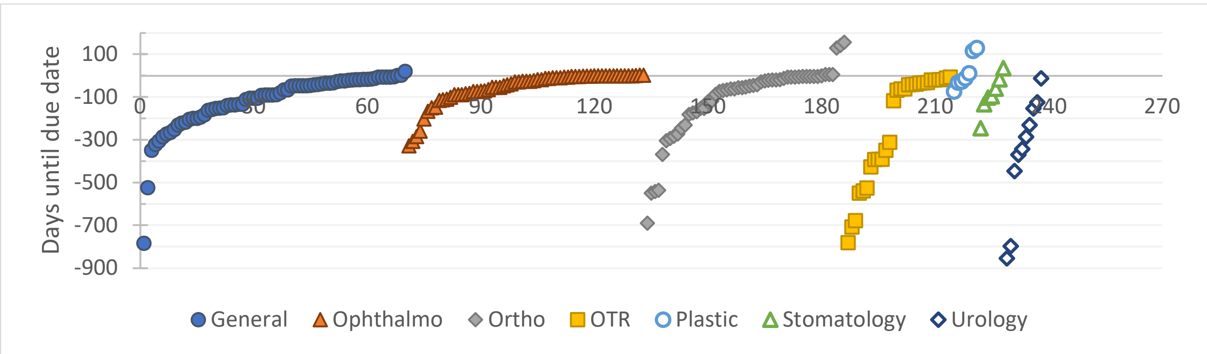
b) Marques and Captivo (2017) – Administration version



c) Marques and Captivo (2017) – Surgeons' version



d) Marques and Captivo (2017) – Mixed version



e) Moosavi and Ebrahimnejad (2020)