Extended Abstract to obtain the Master of Science Degree in
Industrial Engineering and Management

# How to Improve Surgical Production and Stakeholders' Satisfaction? The Portuguese Case of CHLN and HESE

MIGUEL JOSÉ PAES SIMÕES DE SOUSA CABRAL

Department of Engineering and Management, Instituto Superior Técnico, Universidade de Lisboa

miguel.s.cabral@tecnico.ulisboa.pt

**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 decision 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; Stakeholders; Benchmarking; Performance Assessment.

## 1. Introduction

Ensuring health to all citizens is becoming more demanding as the conditions of the population keep changing, due to the rate of population growth, higher life expectancy, and increasing of the elder population proportion. In the last eight years, the demand for surgeries in the Portuguese National Health Service, *Serviço Nacional de Saúde* (SNS), has increased by 23,1% from 2010 to 2018. Even though the number of surgeries performed in SNS has also increased, it is proving difficult to meet demand, with a steady value of 19% more registrations than performed surgeries in the same period (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 operating theatre (OT), several measures can be taken to better optimize the service. The most developed in the literature concerns operating room (OR) planning and scheduling. Nevertheless, developing an optimized schedule that suits all stakeholders is one of the major difficulties for OR managers. Part of these difficulties arises due to numerous complex and conflicting constraints. Also, the objectives to achieve can 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 the 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 test under distinct instances which makes them hard or impossible to directly compare.

The context of impossibility to compare different models and approaches in the current literature motivates the dissertation's research objective of developing a benchmark of OR scheduling models already published in literature. The models are tested using instances from two large public-funded hospitals (Centro Hospitalar Lisboa Norte (CHLN) and Hospital Espírito Santo de Évora (HESE)). The waiting lists (WL) comprise 3 033 and 2 437 episodes, from four and seven specialities, respectively. Additionally, this work has the goal of extending the literature review of Zhu et al. (2019), with the inclusion of new manuscripts released, to obtain an updated and structured literature review on the operational decision level of the OR planning and scheduling problem.

The contributions of this work for the hospitals include: the creation of an evaluation matrix based of different KPIs and a benchmark on selected models to compare the outcome solutions in line with the KPIs, which are valued by the SNS and other hospital stakeholders.

The remainder of this paper is organized as follows: Section 2 proceeds with the presentation of the case studies. Section 3 contains the literature review on the OR planning and scheduling problem, while Section 4 presents the criteria for the selection of the models and the models to partake in the benchmark. Section 5 presents the instances and indicates the benchmark results. Section 6 concludes the paper and gives some future extensions of this work.

## 2. Case Studies

### *2.1 The SNS*

The SNS was founded in 1979 with the primary objective of guaranteeing access and coverage to all population. It is composed by primary care units, hospitals and continuous care units. 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 2020). Since the instances used in the computational experiments are from CHLN and HESE, this work focuses in those two public-funded hospitals.

### *2.2 CHLN*

The CHLN is a central hospital and is located in Lisbon as part of LVT Regional Health Administration (RHA). It is composed by Santa Maria University Hospital, E.P.E. (HSM) and Hospital Pulido Valente, E.P.E. (HPV). The CHLN provides care mainly to the area of Unit of Northern Lisbon with more than 329,000 inhabitants. 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; HSM, stands out for diversity in the various areas of medicine. This 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.

The central OT (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. While HSM serves elective and non-elective surgeries, HPV only has the elective ambulatory surgery service. 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 15,6% of LVT elective surgical production in 2019, where there are 14 other hospital institutions that perform surgery. It is also possible to see in the table that the total number of elective surgeries has been stable from 2014 to 2019, but with a continuous significant decrease in inpatient surgery and an increase in outpatient surgery. This increase in ambulatory surgeries is explained by the pressure from the SNS to opt for this type of surgery whenever possible, since it decreases the time the patient is at the hospital, reducing risk of hospital infections and increasing the turnover of beds.

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

| | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| CHLN | 29,8 | 31,7 | 32,6 | 32,4 | 29,5 | 30,0 |
| Inpatient | 16,2 | 16,2 | 15,6 | 13,3 | 11,2 | 10,5 |
| Outpatient | 13,6 | 15,5 | 17,0 | 19,1 | 18,3 | 19,5 |
| % of LVT RHA | 17,0% | 18,3% | 18,0% | 17,2% | 15,6% | 15,6% |
| LVT RHA | 175,4 | 173,7 | 181,0 | 188,9 | 188,4 | 192,8 |
| Portugal | 546,3 | 552,5 | 565,7 | 575,8 | 572,5 | 604,3 |

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.

### *2.3 HESE*

HESE is a central hospital, located in Évora, Alto Alentejo, being part of the Alentejo RHA. HESE provides direct care to the district of Évora with 152 865 inhabitants and also an area of indirect influence which covers the entire region of Alentejo, corresponding to 319 000 inhabitants.

The number of elective surgical interventions has been in constant growth since 2017 as can be seen in Table 2. In 2019 there were almost 24% more surgeries than 2014. 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 four hospitals performing surgeries. The value of elective production has risen in the last three years, as seen before, but similarly to CHLN, the main increase stands on the ambulatory surgery rather than the conventional. All these surgeries are performed in the COT and correspond to the specialities of general surgery, orthopaedics, urology, ophthalmology, plastic surgery, OTR and stomatology, plus emergencies.

**Table 2** – No. of programmed surgical interventions in HESE, Alentejo RHA and Portugal, in thousands (SICA 2020)

| | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| HESE | 13,5 | 12,6 | 12,7 | 11,6 | 14,6 | 16,7 |
| Inpatient | 4,9 | 5,0 | 4,6 | 4,2 | 4,8 | 5,5 |
| Outpatient | 8,6 | 7,6 | 8,1 | 7,4 | 9,8 | 11,2 |
| % of Alentejo RHA | 52,7% | 49,2% | 46,6% | 45,5% | 52,8% | 56,5% |
| Alentejo RHA | 25,6 | 25,5 | 27,3 | 25,5 | 27,6 | 29,6 |
| Portugal | 546,3 | 552,5 | 565,7 | 575,8 | 572,5 | 604,3 |

### *2.4 Surgery Process in SNS*

In the beginning of the surgery planning process, a care plan for the patient must be designed. The care plan includes the surgical intervention strategy and is developed by the responsible physician to address the patient's problem. When starting the care plan, the patient is pre-registered in the WL 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 2017). The TMRG is based on four clinical priorities, in accordance with the illness itself, among other factors. 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 the list the longest having a higher priority. Also, hospitals are asked to schedule patients two times per week. This is not verified since most hospitals schedule patients on a weekly or fortnightly basis, and online perform punctual online rescheduling if needed (due to no-shows or cancelations).

After being scheduled, the patient is required to be at the hospital for surgery and awaits in preoperative units. In SNS, the surgery teams are composed by two surgeons, one anaesthesiologist, and three nurses, each with a distinct function. Other participants as technical staff are allowed when needed. After the surgery, the patient is sent to a post-anaesthesia care unit or to a recovery units, depending on the patients' condition. When the responsible surgeon considers the patient ready to be sent home, a medical discharge is issued.

### 2.5 *Surgery Stakeholders and Performance Indicators*

Described in Penedo et al. (2015), all OT procedures require multidisciplinary teams, the availability of human resources and their correct management. The main stakeholder in the surgery process is the patient since 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, patients present causes for schedule disruptions, via cancelations and delayed arrivals. Also accounted as a main stakeholder, surgeons are the physicians responsible for performing surgery, being the procedure's outcome highly dependent on the surgeon's expertise. The surgeon concentrates most of the decision-making powers during the surgical procedure, and in the scheduling process. He is accountable for the surgery duration time and the selection of patients to schedule, having a great impact on OR utilization. Besides patients and surgeons, as mentioned, the surgery is also dependent on anaesthesiologist, nurses and other staff. It is important to note that the scarcity of anaesthesiologists is a factor with high impact on surgical production. According to Ramos (2018), the reduced working hours of the COT is mainly related to their shortage. Likewise, Penedo et al. (2015) points to the fact that, in HESE, surgeons and ORs could be more utilized if there were sufficient anaesthesiologists.

In 2013, to assess the OTs with respect to their physical capacity, human resources, production, and quality, 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. 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 were considered suitable to give a complete evaluation of the OT regarding all stakeholders. Currently, this is still the only national assessment of OTs and therefore most performance indicators used in this thesis are extracted from this work. The performance indicators used for the benchmark are present in Section 5.

### 2.6 *Problem Scope Definition*

To improve both the surgical production and stakeholder satisfaction, this study proposes a benchmark of selected models from the literature, by using the same instances, collected from CHLN and HESE. The focus is done on the advance scheduling problem, further detailed in Section 3, 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.

## 3. Literature Review

To address the OR planning and scheduling problem the optimization of ORs has been studied for several years in academic research. OR literature can be divided into three decision levels (Cardoen et al. 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 and creating cyclic schedules or MSSs. Operational decisions are centred in scheduling patients from a WL to a specific day and starting time. This optimization is usually divided into two phases, advance scheduling and allocation scheduling. The remainder of the literature review is divided in four domains: decision levels; patient characteristics; scheduling strategies; and problem features.

### 3.1 *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). As mentioned, the operational decision level is often divided in advance scheduling and allocation scheduling.

**Advance scheduling** consists of selecting the cases from a set of patients registered in a WL, assigning an OR and a specific day within a defined planning horizon. When selecting elective patients from the WL, most authors consider a priority score which prioritizes patients according to the urgency of surgery and the waiting time (Min and Yih 2010; Testi et al. 2007; Valente et al. 2009). Jebali and Diabat (2015) present a case where the admission date of a patient is already scheduled but due to trade-offs between the hospital's resource management and patient-related costs, the surgery can be postponed and the admission date can change.

In most studies, 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). Molina-Pariente, et al. (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 to an OR, or the inverse situation where a patient is assigned to an OR and then a surgeon is allocated to the tuple, pointing that the latter allows more flexibility. To maximize the number of scheduled patients, or to deal with possible stochasticity, some papers allow overtime (Addis et al. 2014; Astaraky and Patrick 2015; Lamiri et al. 2007), even though most authors do not allow it.

The **allocation scheduling** consists of selecting a starting time or sequence definition to each individual surgery (Zhu et al. 2019), although Samudra et al. (2016) also consider the allocation of the ORs. When sequencing patients, Hamid et al. (2019) state that the setup-time for each individual surgery is dependent on the sequence, mainly in surgeries that imply longer times and more critical conditions. The study of different sequencing rules has been investigated by few authors (Liang et al. 2015; Marcon and 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 and Dexter (2006) 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. Khaniyev et al. (2020) focus on assigning starting times for each surgery, considering a given number and sequence of surgeries with uncertain duration.

The **integration of both** advance and allocation scheduling problems has also been studied. Wang et al. (2015) solve the problem by choosing which patients can be operated within the planning horizon and the day of surgery, and then, a sequencing problem, minimizing the number of ORs to open. Developing and solving both phases in a generalized model allows more optimized solutions, although increases the problem complexity. After selecting and assigning surgeries 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.

### *3.2 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). 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 (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 et al. 2017; Testi and Tànfani 2009; Testi et al. 2007; Vali-Siar et al. 2018; Zhang et al. 2019). For handling emergency patients the main policies are dedicated policy and flexible policy (Ferrand et al. 2014; Van Riet and Demeulemeester 2015). In a dedicated policy, specific ORs are used for emergencies (Roshanaei et al. 2017a). The flexible policy can be divided into two - insertion policy, that consists in scheduling an emergency case in-between elective cases (van Essen et al. 2012), and reserved slack, that implies reducing the total capacity of each OR to allow slack for emergencies (Kamran et al. 2019).

The **length of stay** of the patients distinguishes inpatients and outpatients based on the time from the surgery until medical discharge. Outpatients stay in the hospital less than 24 hours and inpatients are required to stay longer. The distinction, however, is rarely done in the literature. 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. In Meskens et al. (2013), alongside with high-priority patients, outpatients should be operated as early as possible, allowing the patient to recover and leave the hospital on the same day without utilizing a bed over-night.

### *3.3 Scheduling Strategies*

When addressing the SSP, different scheduling strategies may be employed, namely block, open and modified block scheduling strategies (Marcon and Kharraja 2003).

**Block scheduling strategy** refers to strategies where surgeons or specialities are allocated to certain time-blocks and patients can only be scheduled in a corresponding block. With this 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 and Captivo 2017). Agnetis et al. (2014), point that some specialities need particular ORs due to special requirements of resources and equipment.

**Open scheduling strategy** allows patients to be scheduled in any OR, without assigning specialities to ORs or time blocks, allowing more flexibility. Abedini et al. (2016) 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 surgeries from different specialities are scheduled in the same OR. To decrease the speciality turnaround time, few researchers use a particular case of the open scheduling strategy, consisting in blocking the OR to the speciality of the first surgery assigned for that day (Castro and Marques 2015). 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 also the idle time of surgeons between surgeries.

The **modified block strategy** presents a compromise between both strategies that lead to a combination of free and reserved blocks. This strategy is rarely studied in literature. Kamran et al. (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, Xie, et al. (2008), where the authors establish semi-open blocks that although assigned to a certain speciality, can have surgeries from other specialities, when there is available capacity, but with a higher cost.

### *3.4 Problem Features*

The classification in this work includes the degrees of uncertainty, a vertical and horizontal integration and the studied objective functions. The SSP have an intrinsic nature of **uncertainty**. The uncertainty in the case duration, most studied, has a large impact both on under- and overtime, that leads to idle time or possible surgery cancellations. To estimate the duration of the cases, researchers often probability distributions. 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 post-anaesthesia care unit time. When dealing with uncertain demand, representing new arrivals, Poisson distributions are used in most papers (Astaraky and Patrick 2015). Erdogan and Denton (2013) consider that the duration and number of surgical cases are uncertain due to tardy cancellations and no-shows. The presence of no-shows is common in outpatient clinics (Lee et al. 2005), creating idle times, resource wastage and underutilization of ORs. The arrival of emergency patients is also important to tackle. A stochastic model is proposed in Lamiri, Xie, et al. (2008) to address the uncertainty in emergency arrivals, considering the capacity required for emergency cases arriving at each moment as a random variable. Besides the use of probability distributions, robust optimization is also used in literature as an approach to deal with stochasticity (Addis et al. 2014; Marques and Captivo 2017; Moosavi and Ebrahimnejad 2018; Rath et al. 2017). 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, assuming that the surgery duration is highly dependent on the assistant surgeon level of expertise. Both Azari-Rad et al. (2014) and Lee and Yih (2014) consider that due to shortage of certain type of resources downstream, the patient path, regarding recovery beds, wards and other postoperative care units can change. Barz and Rajaram (2015) consider that elective and non-elective patients consume different types and quantities of resources.

In **integration**, it is important to distinguish between horizontal and vertical integration. Whereas horizontal integrations accounts for the number of specialities, ORs and possible staff rostering, vertical integration includes the combination of pre- and postoperative units. Although most papers focus in multi-OR problems, when tackling the allocation scheduling in daily basis, exceptions arise (Khaniyev et al. 2020). On the other side of OR integration, Roshanaei et al. (2017a) studies a problem consisting in a network of multiple hospitals, where ORs, patients and surgeons are collaboratively taken into consideration. The problem of nurse rostering alongside with surgical case scheduling has also been subject of concern in the literature (Beliën and Demeulemeester 2008; Bilgin et al. 2012; Xiang et al. 2015a). Regarding vertical integration, few authors consider the patients' stay in the preoperative holding unit before surgery (Jebali et al. 2006; Niu et al. 2013; Schmid and Doerner 2014; Xiang et al. 2015a; Xiang et al. 2015b). 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. Azari-Rad et al. (2014) and Lee and Yih (2014) consider a re-routing in recovery units, when the needed resources are unavailable while some authors consider that the OR becomes blocked and all surgeries are delayed or cancelled until downstream resources are released (Fei et al. 2010; Hamid et al. 2017; M'Hallah and Al-Roomi 2014).

### *3.5 Literature Review Conclusion*

Although each paper brings novel perspectives, instances, and models, to our knowledge, few studies have been implemented in real scenarios. Furthermore, no study has been performed in comparing different existing models, under the same instances. It is possible to conclude that a benchmark with existing models, and instances from real hospitals alongside with objectives compliant with hospital stakeholders' goals should be studied.

## 4. Model Selection and Preliminary Comparison

The selection of the models for the proposed benchmark is a major concern to hospital and particularly OR managers. To select the papers and therefore the models, multiple criteria have been developed, according to the characteristics of the case studies. The papers must meet the following criteria:

- Address the advance scheduling problem;
- Employ block/modified-block scheduling strategies;
- Study the scheduling of elective patients;
- Address multi-OR problems in one hospital;
- Present an explicit mathematical model formulation;
- Only papers from 2010 to 2020 are considered.

From the resulting papers, three papers have been chosen (Kamran et al. 2018; Marques and Captivo 2017; Moosavi and Ebrahimnejad 2020) for their focus on multiple stakeholders, namely focus on the patient, through priority and waiting time, focus on management and focus on surgeons. 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.

Even though addressing the advance scheduling phase of the SSP, each one of the five models encompasses different approaches. For example, ME has a broader spectrum of goals, focusing on tactical decisions as well. Through the adaptation performed in this work, focusing only on part of them can lead to sub-optimal results in the needed objectives. Regarding the considered objectives, it is interesting to analyse which mechanisms are used to schedule patients. MC.Admin considers two distinctive terms for both scheduled and unscheduled patients, removing the linearity, which 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. KKD and ME consider similar cases of having an extra day in the planning horizon where all the episodes that have not been selected are allocated. In ME, 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. This implies that there is no implicit order for selecting patients out of TMRG based on this parameter. The same occurs in KKD for the selected patients, although, for the patients not selected, the actual number of days until due date and priority are considered. By considering a penalization for unscheduled episodes, KKD is expected to schedule more patients than ME and thus reducing the unscheduled list. In an opposite point-of-view, the MC.Sur benefits patients with lower waiting times, selecting the ones which have entered the list more recently. This particularity, even though not providing equity in the selection, is important to be considered as it is expected to mimic the surgeons' real behaviour at the hospitals. For that reason, MC.Mix was developed being a combination of the administration's version for the morning shifts and the surgeons' one in the afternoon shifts. MC.Mix is expected to significantly improve the number of scheduled patients with higher waiting times when compared to MC.Sur, although not reaching the volume of MC.Admin for these patients.

Besides the scheduling of patients, other objectives and restrictions are also considered. Although no limits are established in this work, both KKD and all Marques and Captivo (2017) versions of the model bear into consideration a maximum operating capacity for the surgeons. That parameter is not envisioned in ME but can be highly useful when implementing models in hospitals where capacity limits are imposed. KKD extends the considerations for surgeons with an objective to minimize the number of working days per surgeon as well. Hence, it is expected that the findings present a lower average of working days per surgeon when compared to the others. Also, it includes an objective on the minimization of overutilization, while ME encompasses not only the over- but also the reduction of underutilization. Marques and Captivo (2017), on the contrary do not allow any overutilization in the models.

## 5. Results and Discussion

This section presents the application of the models to CHLN and HESE case studies. 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. The tests were performed in a computer running Windows 10 with an Intel® Core Inside™ i7-6820HQ, four cores, processor of 2.70 GHz and 16 GB of RAM. Having in consideration real-life scenarios, a time limit of 10 minutes was established. The computational experiments are then used for the benchmark.

### *5.1 Evaluation Matrix Formulation*

To perform the benchmark, the evaluation matrix is first formulated. 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. The indicators used are gathered in three groups, namely quality, production and productivity (Table 3). Alongside the indicators, the best solution value for each is also presented. Depending on the KPI, it can be the highest value (HV), lowest value (LV), 100% or zero. It is worth highlighting that the *best solution value* in Table 3 and the *values of reference* chosen in Penedo et al. (2015) have no direct correspondence.

**Table 3** - Selected KPIs by group, 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 |

**Table 4** - Solution values and gaps over the different models

| Instances | Episodes in WL | Blocks in MSS | Model | Solution Value | Gap |
|---|---|---|---|---|---|
| CHLN | 3 033 | 43 | KKD | 431 154 | 0,00% |
| | | | MC.Admin | 774 467 | 0,07% |
| | | | MC.Sur | 630 141 | 0,01% |
| | | | MC.Mix | 775 312 | 0,07% |
| | | | ME | 132 328 | 0,60% |
| HESE | 2 437 | 29 | KKD | 551 728 | 0,00% |
| | | | MC.Admin | 578 521 | 0,02% |
| | | | MC.Sur | 380 038 | 0,09% |
| | | | MC.Mix | 592 552 | 0,03% |
| | | | ME | 169 290 | 0,02% |

### *5.2 Case Studies Results*

The computational experiments showed that with the enforcement of a time limit, most models did not reach the optimal solution, presenting a feasible solution and the respective gap (Table 4). When comparing the results, the value of the solution value for any model has no significance as each objective function is different.

Both instances used in the tests are detailed in Table 5. It is important to highlight that the surgery and room duration times in CHLN instance are calculated using the average utilization times from the surgical record of 2013 to 2015. Whereas the room duration accounts for the time on the OR, the surgery time indicates the time in which the surgeon is needed. In HESE, the duration was already present in the WL and only room duration was accounted. Furthermore, data of the actual surgical plan for the week under consideration in CHLN was also given. Hence it is possible to compare the results of with the actual scheduling plan for CHLN.

#### *5.2.1 Intra-Indicators Analysis*

All models have successfully scheduled patients from a total of 3 033 and 2 437 patients in the WL of CHLN and HESE. Regarding number of scheduled patients (Table 6), the findings show that in CHLN the best results is achieved by MC.Sur with 109 patients scheduled. It is also the model that sched-

**Table 5** – Instances' characteristics for CHLN and HESE

| Instance | Speciality | Days | M shifts | A shifts | No. of surgeons | No. of episodes WL | Avg. surgery duration | Avg. room duration | Avg. episode due date |
|---|---|---|---|---|---|---|---|---|---|
| CHLN | GEN | 5 | 10 | 5 | 48 | 526 | 78,4 | 155,9 | 104,9 |
| | ORT | 5 | 9 | 1 | 30 | 894 | 125,2 | 228,9 | 2,6 |
| | URO | 5 | 5 | 3 | 31 | 572 | 57,9 | 122,9 | 64,0 |
| | VAS | 5 | 5 | 5 | 29 | 1 041 | 79,2 | 150,4 | 5,4 |
| HESE | GEN | 5 | 6 | 4 | 21 | 711 | - | 51,8 | 33,0 |
| | PLA | 1 | 0 | 1 | 3 | 285 | - | 29,5 | 111,3 |
| | STO | 1 | 1 | 0 | 3 | 14 | - | 33,9 | -85,5 |
| | OPH | 4 | 4 | 0 | 14 | 650 | - | 15,7 | 54,0 |
| | ORT | 5 | 8 | 0 | 6 | 240 | - | 46,0 | 42,9 |
| | OTR | 2 | 0 | 2 | 7 | 301 | - | 39,9 | -150,6 |
| | URO | 1 | 0 | 1 | 4 | 236 | - | 37,6 | -203,4 |

**Table 6** – Model findings on episode scheduling for CHLN and HESE

| Instance | Model | No. of scheduled episodes | Priority | | | Tardy episodes | | Avg. no. of days until TMRG | |
|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | Absolute no. | % of Sched. | Scheduled Surgeries | Surgeries not scheduled |
| CHLN | Total in WL | 3 033 | 2 949 | 63 | 21 | 943 | 31,10% | - | - |
| | Plan | 82 | 63 | 16 | 3 | 10 | 12,20% | - | - |
| | KKD | 108 | 81 | 13 | 14 | 86 | 79,63% | -67,88 | 36,63 |
| | MC.Admin | 93 | 63 | 14 | 16 | 76 | 81,72% | -252,91 | 41,95 |
| | MC.Sur | 109 | 109 | 0 | 0 | 0 | 0,00% | 162,54 | 28,08 |
| | MC.Mix | 100 | 71 | 13 | 16 | 71 | 71,00% | -203,76 | 40,98 |
| | ME | 92 | 89 | 2 | 1 | 41 | 44,57% | -25,33 | 34,73 |
| HESE | Total in WL | 2 437 | 2 178 | 211 | 48 | 765 | 31,39% | - | - |
| | KKD | 268 | 180 | 43 | 45 | 185 | 69,03% | -50,70 | 9,06 |
| | MC.Admin | 230 | 128 | 57 | 46 | 180 | 78,26% | -221,93 | 25,88 |
| | MC.Sur | 274 | 266 | 8 | 0 | 1 | 0,36% | 134,58 | -14,24 |
| | MC.Mix | 242 | 117 | 81 | 44 | 162 | 66,94% | -123,90 | 16,42 |
| | ME | 238 | 187 | 20 | 31 | 222 | 93,28% | -120,80 | 15,83 |

ules more patients with HESE instance (274 patients). Although the number of blocks in HESE is lesser than in CHLN (Table 4), a shorter average surgery time for HESE surgeries (36,0 minutes compared with 169,3 minutes in CHLN) is deemed as the reason for a higher number of patients scheduled in HESE. The rest of the models follow the same pattern, with ME and MC.Admin achieving the worst result in CHLN (92 and 93 patients, respectively) and HESE (238 and 230 patients, respectively). Through Table 6 it is also possible to see that the actual plan from CHLN schedules 82 patients. 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 plan are used as guidelines and cannot be compared directly.

However, Table 6 shows that the CHLN plan schedules patients from priority two and one have whilst priority three patients were still on the WL, demonstrating that the SNS guidelines on scheduling priorities are not being followed. MC.Sur, as expected, fails to schedule priority two and three from the WL, whereas the best results are shown by MC.Admin and MC.Mix. The variations in the findings of ME between both tests regarding the priorities, 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.

Besides the surgery priority, the time in the WL and the time until due date/TMRG is also an important factor. Table 6 indicates the number of tardy scheduled surgeries, which already passed TMRG. The value for the CHLN plan shows that only 12% of the patients selected are out of due date, although there are 943 in the WL, which contributes for the high number of tardy episodes in the WL. 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 plan. On the other end, the KKD 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%) for CHLN. 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. 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. However, ME presents the best result using HESE data, with 222 tardy patients scheduled (93,28%). This different behaviour shows that, by changing the testing samples, findings can differ. 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 findings of CHLN – KKD has the highest number of tardy scheduled episodes, even though MC.Admin has a higher ratio between tardy and total scheduled episodes. Unfortunately, the surgical plan of HESE for the week under study was not provided, so a comparison with their data is not possible.

Selecting patients with higher waiting times leads to a WL 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 WL for the next planning horizon is going to be. In Table 6 it is also possible to observe how the average of days until TMRG for surgeries not scheduled varies accordingly to the value for scheduled surgeries in both scenarios. Please note that negative values have already passed the TMRG. In both tests MC.Sur, despite having more surgeries scheduled, has the lower average of days until TMRG (which corresponds to a higher waiting time), since almost 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 WL). Attending to the evolution of the WL 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 WL, which relates to the scheduling order followed by the surgeons.

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 for hospital administrations, as a stakeholder. 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, and great dissatisfaction of patients. As no overtime was allowed in the experiments, all of the models have under 100% occupation rates, however, with different degrees of underutilization (Table 7). 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. Despite the difference in CHLN on the amount of total underutilization being 82% from best (MC.Mix) to worst result (MC.Sur), the difference of the results, when analysing the values translated in percentage of OR occupation becomes more subtle, with a difference of 2,1 percentual points.

On the opposite side, the CHLN Plan has a negative value for underutilization as can be seen in Table 7, which is equivalent to 166,8 minutes of total overutilization. However, despite having an average OR occupation rate of only 101,1%, the plan has the largest discrepancies among specialities, as seen in ΔMmU. 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. The findings using HESE data show a better use of the capacity, with a significant reduction of underutilization (Table 7). It is presented the possibility that by having much shorter surgery durations compared to CHLN, as mentioned, more combinations of different episodes that provide lesser block underutilization are possible in HESE. In this scenario, ME 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. Regarding the cleaning time, since it is considered 20 minutes of cleaning time per surgery, it is proportional to number of surgeries itself. For that reason, the gaps of the values with and without cleaning time in MC.Sur and KKD are larger than the rest of the models. Analogously, since all models are able to schedule more episodes using HESE instances, more cleaning cycles are needed per block, presenting smaller occupation without cleaning time.

**Table 7** - Underutilization and occupation results

| | | U | ΔMmU | AvUB | %OR | AvTCT | AvTnCT |
|---|---|---|---|---|---|---|---|
| CHLN | Plan | -166,8 | 2 457,2 | -3,9 | 101,10% | 363,6 | 325,5 |
| | KKD | 716,4 | 139,6 | 16,7 | 95,40% | 343,3 | 293,1 |
| | MC.Admin | 428,1 | 146,5 | 10,0 | 97,20% | 350,0 | 306,8 |
| | MC.Sur | 727,5 | 597,7 | 16,9 | 95,30% | 343,1 | 292,4 |
| | MC.Mix | 399,5 | 101,1 | 9,3 | 97,40% | 350,7 | 304,2 |
| | ME | 633,0 | 216,0 | 14,7 | 95,90% | 345,3 | 302,5 |
| HESE | KKD | 147,0 | 67,0 | 5,1 | 98,59% | 354,9 | 170,1 |
| | MC.Admin | 30,0 | 11,0 | 1,0 | 99,71% | 359,0 | 200,3 |
| | MC.Sur | 114,0 | 75,0 | 3,9 | 98,91% | 356,1 | 167,1 |
| | MC.Mix | 30,0 | 15,0 | 1,0 | 99,71% | 359,0 | 192,1 |
| | ME | 19,0 | 8,0 | 0,7 | 99,82% | 359,3 | 195,2 |

U – Underutilization; ΔMmU – $|\max_{\top specialities} U - \min_{\top specialities} U|$; AvUB – Avg. Underutilization per block; %OR – OR occupation rate; AvTct – Avg. Occupation time with CT; AvTnct – Avg. Occupation time without CT

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 (Table 8). Being the only paper that incorporates the objective of reducing the number of surgeon's working days, KKD presents the best results in both CHLN and HESE tests. It is important to mention that this average only takes into consideration surgeons that are planned for the week, not accounting for surgeons without surgeries planned. The low value of CHLN plan, compared to the models' findings may be related with the actual planning at the hospital with surgeons' pre-established schedules that are not taken into consideration in the models. As can be seen, the number of required surgeons has no direct impact on the average number of working days per surgeon, being possible to conclude that having more surgeons performing surgeons does not reduce the workload, in terms of days, for those surgeons and vice versa. MC.Sur, although trying to represent the real scenario at hospitals and the surgeons' perspective, does not accomplish the objective on this parameter. Although the differences between models present small variation in CHLN (a difference of 0,37 days between best and worst result), the findings became more evident under HESE instances. In fact, in HESE, KKD 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.

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. Unfortunately, the establishment of such is out-of-scope in this work and is presented as recommendations and future work. The following concludes the results' discussion, with an overview of the results of each model regarding the KPIs and discussing the results inter-KPIs.

**Table 8** - Surgeon utilization

| | | No. of Surgeons | Avg. No. of WD per Surgeon |
|---|---|---|---|
| CHLN | WL | 148 | - |
| | Plan | 42 | 1,19 |
| | KKD | 46 | 1,36 |
| | MC.Admin | 49 | 1,57 |
| | MC.Sur | 49 | 1,73 |
| | MC.Mix | 53 | 1,55 |
| | ME | 45 | 1,73 |
| HESE | WL | 58 | - |
| | KKD | 44 | 1,88 |
| | MC.Admin | 40 | 2,40 |
| | MC.Sur | 48 | 2,60 |
| | MC.Mix | 45 | 4,43 |
| | ME | 42 | 2,38 |

### *5.2.2 Overview and Inter-Indicators Analysis*

Since no value functions are assigned to the KPIs, 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. The average, to assess the performance of the models' results, and the variation, to assess the consistency of the results amongst tests is presented in Fig. 1. In a general analysis, overviewing together all indicator groups, it is visible that the performance of each model also varies according to the groups. 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, although probably at the cost of the performance in production and productivity related indicators. 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. 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, ME has a lower performance, not achieving any best score. The lower performance can be the consequence of being a model built towards a broader spectrum of objectives and parameters, which is adapted for this work, compromising the performance of the results. Nevertheless, 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.

## 6. Conclusions and Future Work

The SSP are complex problems that require coexistence and interaction of multiple stakeholders. 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 has represented 120% of the production capacity. The optimization of

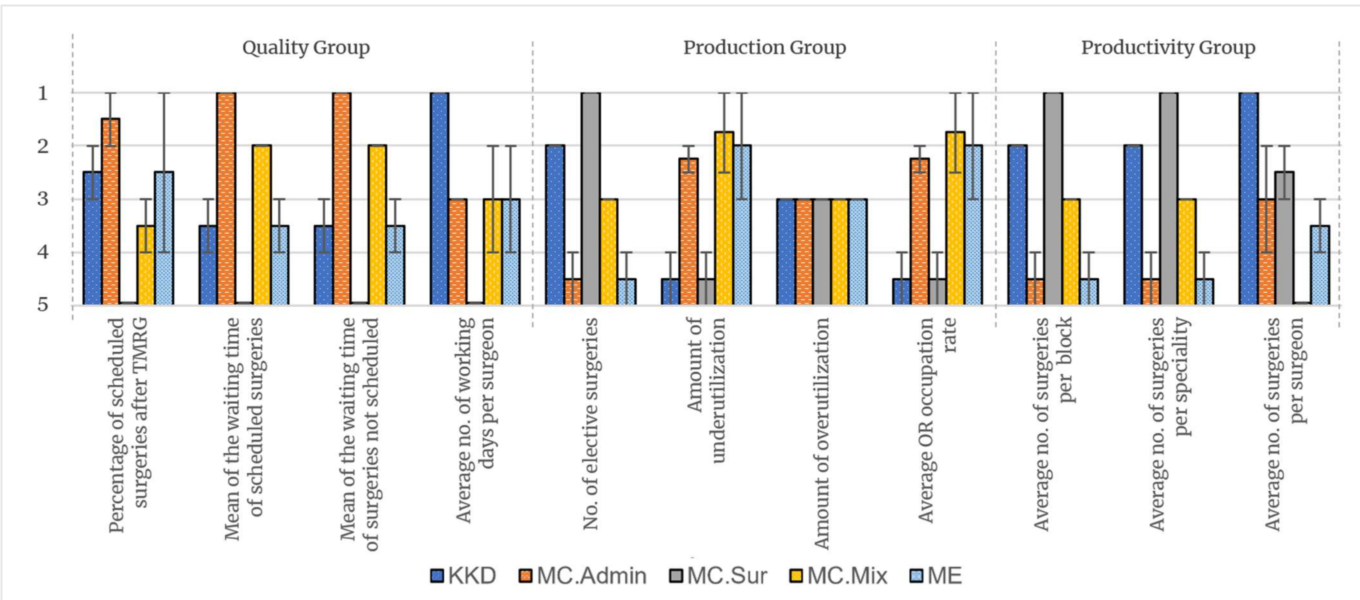


**Fig. 1** - Overall model results (ranked from 1 to 5) and respective variation on the selected KPIs

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.

This dissertation has the objective of establishing a general matrix of KPIs that allow the measurement of the surgical production and the satisfaction of different stakeholders, namely patients, surgeons and the hospitals' administration, through quantitative criteria. A benchmark is also developed with three papers from the analysed literature (Kamran et al. 2018; Marques and Captivo 2017; Moosavi and Ebrahimnejad 2020), for their coverage on those stakeholders. The paper of Marques and Captivo (2017) comprises three different models. 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). Although all models present feasible results, the quality of the solutions according to the defined matrix of KPIs 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). The distinction between MC.Sur and the remaining models is clear 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, it is recommended that MC.Sur is not included in the group of models that can be adapted by SNS to schedule surgeries. All the other models have performed fairly, with the administrations' version showing a clear focus on selecting the patients with higher waiting times. Nevertheless, the findings of Kamran et al. (2018) and Moosavi and Ebrahimnejad (2020) show a higher number of tardy patients scheduled. In some indicators, a variation between the findings of the computational experiments using CHLN and HESE is observed. These variations show that testing only two instances may compromise the accuracy of the findings from a statistical point-of-view. Variations are more prominent on the underutilization KPI, where no model achieved a stable score between tests.

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. To improve the present work, future work suggestions include: a) creating a decision-support model to establish value functions for each indicator and determine the weight of each KPI according to the decision maker perspective; b) further testing with instances from other hospitals or different years to ensure that the variations amongst models' findings are reduced; c) considering pre- and postoperative units, as their scarcity often changes the applicability of the findings; d) considering other stakeholders in the perioperative stage, such as anaesthesiologists and nurses, since they can be limiting factors in surgical production; e) reviewing of the strategic metrics used in the payment contracts so that the optimized surgical production meets the parameters asked by the SNS.

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