Operating room planning and scheduling for outpatients and inpatients: A review and future research

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Abstract

In hospitals, surgeries are treated either on an outpatient or on an inpatient basis. Outpatients are normally routine patients that enter and leave the hospital on the same day, while inpatients who need more complex surgeries have to stay overnight. More recently, a shift from inpatient surgery to outpatient surgery is occurring due to scientific progress in anaesthesia and surgical techniques. Identifying possible similarities and differences between outpatient surgery scheduling and inpatient surgery scheduling can serve as a valuable decision-making foundation for practitioners and for operations researchers to efficiently schedule patients for surgery in the surgical department. This paper provides the first literature review on comparing outpatient surgery scheduling with inpatient surgery scheduling. The literature published between 2000 and 2020 that explicitly mentions either scheduling setting is included and it is analyzed from three dimensions, i.e., the uncertainty incorporation, the research methodology, and a scheduling performance comparison between both settings. We find that outpatient surgery can observe better results in many of the performance measures (i.e., operating room utilization, overtime, and patient cancellation rate) as opposed to inpatient surgery. This is due to the fact that inpatient surgery duration is longer and more variable and to the presence of more emergency patients, although there is a higher likelihood of no-shows for outpatients. Moreover, we identify future research directions that provide opportunities for expanding existing methodologies and especially for narrowing the gap between theory and practice.

Keywords: Health care management, Operating room planning, Surgery scheduling, Outpatient surgery, Inpatient surgery, Literature review

1. Introduction

In hospitals, the operating rooms (ORs) are one of the most critical and expensive resources and many patients undergo a surgical intervention in their care pathway [82, 91]. Ideally, the surgical services would

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be able to deliver the highest quality of surgery to the right patient at the right time. However, due to the randomness and complexity inherent to surgical processes, OR schedules often cannot be executed as planned [173, 180]. Thus, the efficient scheduling of the ORs has attracted much attention from both researchers and practitioners during the last few decades.

Additionally, surgeries are treated either on an inpatient basis or on an outpatient basis in hospitals. Inpatients are hospitalized patients who have to stay overnight after surgery, whereas outpatients are normally routine patients with predictable requirements that enter and leave the hospital on the same day (typically a stay of 4-6 hours). In this respect, it seems that the more routine surgery activities in an outpatient setting could be planned and scheduled more effectively, whereas it is hard to guarantee the same performance in the inpatient surgical department. In terms of facilities, unlike inpatient surgery, outpatient surgery can be performed in hospital outpatient departments, freestanding ambulatory surgery centers (ASCs), or in office-based surgeries [145]. These features imply that the planning and management of surgeries in both settings are substantially different. Identifying possible differences and analogies between the inpatient and the outpatient surgery settings can serve as a valuable decision-making foundation for practitioners and for operations researchers to efficiently schedule patients for surgery in the surgical department. This might also provide important insights for dealing with the complexity and randomness inherent to surgical processes by incorporating some of the advantages that have already been shown to be effective. Therefore, this paper aims to perform a thorough and focused literature review comparing and contrasting the inpatient and outpatient scheduling settings.

This is particularly the case when one considers the broader secular trends occurring in the healthcare delivery industry and in the management of surgeries. Outpatient surgery rates have gradually increased in many countries over the last few decades. For example, in the United States, recent years have observed an increase in the percentage of surgeries that are performed in outpatient settings (compared to 58% in 2005) [73]. In the United Kingdom (UK), the list of surgical procedures deemed suitable and safe on a same-day basis has expanded from 20 in 1990 to over 200 procedures in 2019 [17]. Many European countries have also seen obvious trends in the adoption of day surgery for a growing number of interventions since 2005, e.g., Denmark, Finland, Sweden, and Netherlands [174]. Reasons for the increasing popularity of outpatient surgery are various: medical, economic, and organizational. First, the shift has been facilitated by scientific progress in anaesthesia and surgical techniques. Moreover, outpatient surgery is associated with smaller hospital-acquired infection rates and lower surgery cancellation risks than those encountered following inpatient surgery [97, 146]. Second, outpatient surgery is cost-effective compared to inpatient surgery since hospitalization time is reduced [97, 146]. Third, the consequences of the transition to outpatient surgery seem to be win-win for all parties involved [146].

Apart from the general motivations, this review is also inspired by University Hospitals Leuven (among the largest hospitals in Europe) which is a reference hospital in Belgium where patients are often referred to from other hospitals. The university hospital indicates that the next big improvement in the scheduling of their inpatient operating theater (OT) probably is to treat some of the inpatients in the way their outpatients are treated since they already have an efficient outpatient clinic. The practical reasoning behind this is that its outpatient clinic normally performs routine and more predictable day-care surgeries, whereas long and complex surgeries are performed in the inpatient OT. In order to obtain more comprehensive insights from the literature, we will carefully consider the similarities and differences between inpatient surgery scheduling and outpatient surgery scheduling. Specifically, we will consider how these were observed in the different papers that referred to elements of such situations in different hospitals.

OR planning and scheduling is an extensively studied area and the literature has been reviewed by many authors, using various classification frameworks (see Table 1). These frameworks are either comprehensive (i.e., according to the hierarchical decision levels [82, 91] and/or the custom fields [46, 155, 211]) or focused on a specific topic (e.g., a specific decision level [93] and a specific solution approach [163]). For example, Cardoen et al. [46] and Samudra et al. [155] review the literature in a systematic and comprehensive framework based on multiple descriptive fields, e.g., patient characteristics, uncertainty, methodology, and performance measures. By limiting the scope to a higher decision level, Hof et al. [93] provide a literature review exclusively focusing on the case mix planning problem. Methodologically, Soh et al. [163] review the literature on the application of simulation models in hospital-wide surgical services. To get insights into managing OR efficiency and responsiveness for both elective and non-elective (e.g., emergency) surgeries, a detailed review on OR planning and scheduling between both surgery types is conducted by Van Riet and Demeulemeester [184] and Ferrand et al. [71].

Table 1: Overview of existing literature reviews on OR planning and scheduling

Authors (year)	Compre-hensive	Focused on	Hierarchical levels	Custom fields
Cardoen et al. (2010) [46]	✓			✓
Guerriero and Guido (2011) [82]	✓		1-4	
May et al. (2011) [129]	✓		1-4	
Abdelrasol et al. (2014) [1]	✓		1-3	
Samudra et al. (2016) [155]	✓			✓
Zhu et al. (2019) [211]	✓		1-3	✓
Dexter et al. (2004) [60]		Single decision level	4	
Gupta (2007) [85]		Solution approaches	1-3	
Erdogan and Denton (2011) [67]		Solution approaches		
Hans and Vanberkel (2012) [91]		Solution approaches	1-3	
Samudra et al. (2013) [153]		Research groups		
Ferrand et al. (2014) [71]		Elective/non-elective	2,3	
Van Riet and Demeulemeester (2015) [184]		Elective/non-elective	2,3	
Hof et al. (2017) [93]		Single decision level	1	
Soh et al. (2017) [163]		Simulation application		
Our review		Outpatient/inpatient		✓

Notes. Hierarchical levels [91]: 1 strategic level; 2 tactical level; 3 offline operational level; 4 online operational level. *Custom filelds* include multiple descriptive fields [155], e.g., patient characteristics, uncertainty, methodology, and performance measures.

Similarly to Cardoen et al. [46] and Samudra et al. [155], we classify the articles based on the different descriptive fields. Three important classification fields are involved: the uncertainty incorporation, the research methodology, and a performance comparison between the two scheduling settings. We use these classification fields since they can describe the major profile of the scheduling problem, i.e., what are the problem characteristics, how is the scheduling problem solved, and especially, what are the outcomes of the performance measures (PMs). Our review is different from the previous literature reviews in that for each classification field in this review, we further distinguish an inpatient setting and an outpatient setting in order to investigate whether the scheduling performance in either setting is different and why this happens. It is helpful for researchers to quickly learn about the key characteristics in each surgery setting and to consider key factors when improving the scheduling of ORs. This especially holds true if the OR manager expects to implement the technique that is developed by the researcher.

This paper is structured as follows. Firstly, Section 2 gives the literature search method along with results of metadata statistical analysis. In Section 3, papers are classified by the incorporated uncertainty and the modeling assumptions. Section 4 discusses various research methodologies applied in the literature. In Section 5, we investigate in the literature whether the scheduling performance is different between both settings. Section 6 provides ideas for future research along with specific suggestions for efficient inpatient surgery scheduling. Finally, Section 7 provides a summary of this paper and describes our main conclusions. The list of important abbreviations is reported in Appendix A.

2. Literature search methodology

2.1. Literature collection and identification

We used a structured literature search method (see Table 2) to ensure that we found key and state-of-the-art contributions under the scope of this review. First, we performed an initial search for academic papers that discuss OR planning and scheduling. For this, we identified relevant search terms and we used wildcards in the search terms. With these search terms, we searched for academic papers from January 2000 to December 2020 based on the database of Web of Science (WoS). WoS was chosen as it provides the possibility to select Operations Research & Management Science (OR&MS) and Health Care Sciences & Services (HCS&S) as specific subject categories and to sort search results on the number of citations. Refer to the WoS Core Collection (i.e., https://mjl.clarivate.com/home) for a full list of journals within OR&MS and HCS&S. We searched in titles, abstracts and keywords for related academic literature, written in English. Both peer-reviewed articles and conference proceedings were included in this review.

Then, we selected a base set containing the 20 most-cited articles. Based on this base set, we identified all articles that are referred by or refer to one of the articles in the base set and deal with OR planning and scheduling. We found some journals that are particularly relevant for OR planning and scheduling but are outside the OR&MS and HCS&S subject categories, i.e., anesthesiology/surgery-related journals (e.g., Anesthesia & Analgesia), health policy-related journals (e.g., Health Care Management Science and Health Systems), and engineering-related journals (e.g., Computers & Industrial Engineering and IISE Transactions

Table 2: The literature search method

Step	What to do
Step 1:	Identify search terms: '(operating room$ $\vee$ operating theat* $\vee$ operating suite $\vee$ surger* $\vee$ surgical) $\wedge$ (scheduling $\vee$ planning)'
Step 2:	Search the subject categories of OR&MS and HCS&S in WoS with the search terms
Step 3:	Select a base set: the 20 most-cited articles relevant for our review
Step 4:	Perform a backward and forward search on the base set articles
Step 5:	Access other relevant online bibliographies and sources
Step 6:	Include the literature that explicitly incorporates inpatients/outpatients in the final set

Notes. A search engine can replace $ by zero or one character. A search engine can replace '*' by any group of characters, including no character.

on Healthcare Systems Engineering). Thus, we further included the articles published in these journals at this forward and backward search stage.

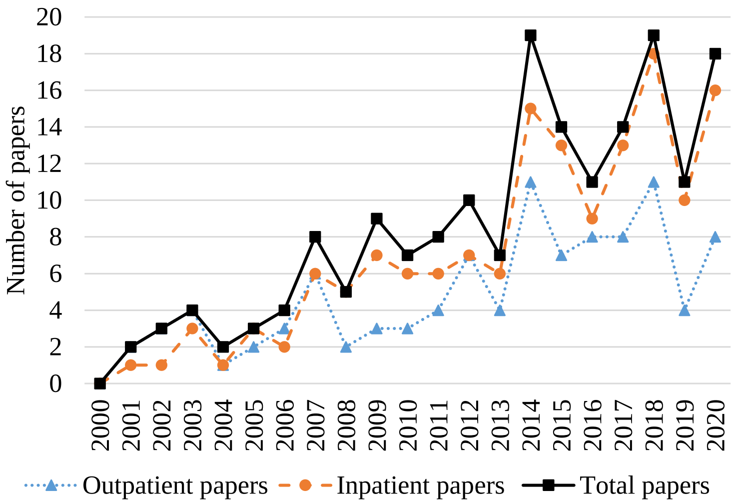
On top of the above database, we also accessed a comprehensive and up-to-date online bibliography on surgical services management maintained by Dexter [57] as well as an online bibliography of the literature in the field of Operations Research/Management Science in Health Care (i.e., ORchestra) [95]. Furthermore, we referred to the search results of Samudra et al. [155]. We checked each article on these sources and identified the literature on OR planning and scheduling. Papers that cannot be accessed on the website were obtained by personal communication with the authors. After the search process, we identified 393 technically oriented papers. Here, the 'technical' papers are those that contain operations research techniques (e.g., mathematical modeling and simulation) or detailed algorithmic descriptions.

Starting from this initial set of papers, the literature that explicitly incorporates either inpatients or outpatients is identified and is included in the final set. Specifically, we use the following two filter criteria: (1) inpatient-related terms (e.g., 'inpatient', 'hospitalized', and 'overnight stay') or outpatient-related terms (e.g., 'outpatient', 'ambulatory', and 'day-care') are used in the paper; (2) if not, the assumptions about the length of stay (LOS) of patients will be checked to distinguish whether the LOS is at least 1 day or not.

As a result, 215 technical papers are excluded and the final set involves 178 technical papers (77 inpatient papers, 30 outpatient papers, and 71 papers considering both aspects). Papers that only mention incorporating elective patients but do not indicate what type of elective patients (inpatients or outpatients) are not included. Moreover, other data-analysis related papers were selected if they compare the performance between an inpatient setting and an outpatient setting. Some managerial papers are excluded from the classification tables but are mentioned if they provide specific insights.

2.2. *Metadata statistical analysis*

Figure 1 shows the number of annually published papers from 2000 to 2020. It is clear that the topic on OR planning and scheduling (in both patient settings) is becoming increasingly popular in the literature, whereas the overall number of outpatient papers is smaller than that of inpatient papers. Furthermore, there are 49 peer-reviewed journals in total publishing the selected papers. Figure 2 shows the journals with more than 3 publications on this topic. As can be observed, European Journal of Operational Research is the leading journal on this topic with 18 papers.



Notes. Papers that consider both outpatient and inpatient surgery are counted in both categories (outpatient and inpatient), but only counted once when computing the total number.

Figure 1: The number of published papers growing over the last 2 decades

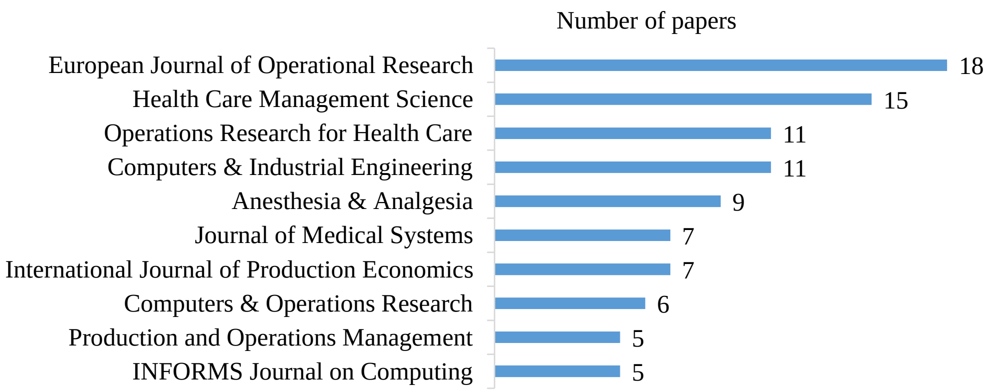


Figure 2: The number of published papers per peer-reviewed journal

3. Activity uncertainty and modeling assumptions

One of the major problems associated with OR planning and scheduling is uncertainty which is the stochasticity in terms of the duration of different activities in the surgical delivery process. Table 3 divides the literature according to the patient type (inpatient versus outpatient). In addition, it classifies the literature of each of the two patient types according to the uncertainty which is inherent to patient demand (i.e., Section 3.1), surgery durations (i.e., Section 3.2) and length of stay (i.e., Section 3.3), etc. Out of the reviewed papers, about 66% incorporate some sort of variability and the surgery duration uncertainty is most frequently taken into account in both settings.

Table 3: Stochasticity considered in the literature for inpatient and outpatient settings

	% of papers	Inpatient setting	Outpatient setting
Deterministic	34% (48/35)	[4, 5, 7, 9, 11, 12, 14, 16, 19, 24, 28, 35, 40, 42, 47, 48, 51, 78, 87, 89, 98, 99, 102, 107, 111, 123, 126–128, 135, 142–144, 152, 156, 159, 164, 166, 171, 172, 181, 186, 187, 189, 191, 193, 199, 200]	[4, 5, 12, 16, 19, 24, 29, 35, 44, 45, 47, 58, 65, 72, 78, 79, 87, 94, 111, 115, 123, 126–128, 135, 138, 143, 144, 152, 156, 189, 191, 195, 200, 210]
Demand	33% (51/30)	[2, 13, 15, 21, 22, 25–27, 30, 36, 38, 43, 50, 52, 53, 63, 68, 70, 74, 80, 86, 88, 101, 103, 105, 106, 109, 117–121, 130, 134, 147, 148, 154, 161, 162, 169, 177, 179, 183, 185, 188, 190, 192, 201–203, 212]	[15, 22, 33, 34, 36, 38, 39, 43, 50, 63, 68, 70, 86, 103, 109, 117, 119, 120, 149, 151, 161, 169, 170, 177, 185, 190, 192, 196, 201, 202]
Duration	54% (79/54)	[3, 6, 8, 13, 15, 18, 20, 22, 23, 26, 27, 30, 36, 38, 41, 43, 49, 53, 55, 63, 68, 69, 74, 80, 86, 88, 90, 100, 101, 105, 106, 109, 112–114, 117, 119–122, 124, 125, 130–134, 136, 139, 141, 147, 148, 150, 154, 160, 165, 167, 169, 173, 175–177, 179, 180, 182, 183, 185, 188, 192, 197, 201–204, 206–209, 212]	[6, 8, 10, 15, 18, 22, 33, 34, 36, 38, 39, 43, 49, 54–56, 63, 68, 69, 81, 83, 84, 86, 96, 109, 113, 114, 117, 119, 120, 122, 124, 125, 132, 133, 136, 149–151, 157, 167, 169, 170, 173, 175, 177, 185, 192, 194, 196, 197, 201, 202, 205]
LOS (PACU, ward, and ICU)	30% (48/18)	[2, 3, 13, 20, 23, 26, 27, 30, 31, 36, 37, 41, 53, 68, 69, 74, 76, 77, 88, 92, 100, 101, 110, 113, 116, 118, 121, 130, 132, 134, 139, 141, 158, 160, 162, 165, 169, 175, 176, 178, 182, 185, 188, 192, 197, 203, 204, 212]	[56, 68, 69, 76, 84, 92, 96, 113, 116, 132, 149, 151, 157, 158, 169, 175, 192, 197]
Others	19% (25/22)	[6, 13, 23, 36, 41, 43, 68, 69, 74–77, 86, 88, 106, 114, 119, 121, 131, 132, 141, 158, 160, 173, 190]	[6, 34, 36, 43, 56, 61, 68, 69, 75, 76, 84, 86, 96, 114, 119, 132, 149, 151, 157, 158, 173, 190]

Notes. PACU: post-anesthesia care unit. ICU: intensive care unit. Others include turnover, preparation, etc. The two numbers in parentheses following each percentage represent the number of inpatient papers and of outpatient papers, respectively.

3.1. Patient demand

The patient demand arrival represents the time point when the request for surgery arises at the hospital. In order to model the volatile patient demand patterns, a majority of studies use historical data. Table 4 shows that the Poisson distribution is often utilized for both inpatients and outpatients in the literature.

That is, the inter-arrival times between successive patients' requests are often modeled as the exponential distribution [36, 63, 201]. The patient arrival pattern depends on the patient type (i.e., outpatient, inpatient, and non-elective), the clinical discipline, and time, etc [86, 154, 201]. Holidays, for example, in a week lead to smaller arrival numbers for all surgery disciplines [154]. Moreover, the patient arrival pattern is sometimes modeled as a non-stationary process with the arrival rate changing over time [86, 118, 121, 201]. For instance, Zhang et al. [201] assume the outpatient arrival process for each specialty to be a non-stationary Poisson process in their case hospital, while a stationary Poisson process is assumed for the inpatient and emergency patient demands. Gupta et al. [86] take into account seasonal and day-of-week variations in patient arrival rates.

Table 4: Assumptions on the probability distribution of surgery durations and demand

	Surgery duration		Patient demand arrival	
Inpatient	Lognormal	[6, 20, 41, 63, 68, 69, 74, 88, 100, 101, 112, 113, 117, 119, 122, 132, 133, 139, 147, 148, 167, 169, 173, 175, 176, 179, 182, 183, 188, 192, 201, 203, 204, 206–209]	Poisson	[2, 13, 36, 52, 53, 63, 74, 80, 88, 101, 103, 109, 118, 121, 130, 148, 162, 179, 188, 201–203]
	Empirical	[23, 36, 41, 125, 141, 154, 190]	Normal	[8, 183, 190]
	Normal	[131, 160, 180, 197, 207]	Uniform	[68, 103, 117]
	Uniform	[121, 165, 206]		
	Exponential	[13, 80, 202]		
	Other	[68, 105, 106, 136, 206]		
Outpatient	Lognormal	[6, 34, 54, 63, 68, 69, 81, 84, 113, 117, 119, 122, 132, 133, 157, 167, 169, 170, 173, 175, 192, 194, 196, 201, 205]	Poisson	[36, 63, 103, 109, 119, 151, 196, 201, 202]
	Empirical	[36, 56, 125, 190]	Uniform	[68, 103, 117, 149]
	Normal	[8, 54, 149, 197]		
	Weibull	[68, 149]		
	Other	[54, 68, 136, 149, 157, 202]		

After patients are scheduled for surgery, many papers assume that patients are punctual to their appointments. However, in reality, patients sometimes do not punctually arrive at the hospital or even do not show up at the planned time of surgery (called a no-show), which is especially true for outpatients. Outpatient no-show is studied in some papers by assuming a no-show probability that ranges from 5% to 24% [34, 38, 39, 68, 201], while there is even less research on the unpunctuality of outpatients (e.g., late arrival) in the literature [39, 43, 68, 170]. No-show is not common for inpatients, since inpatients might be admitted in the hospital some days before surgery due to, e.g., necessary pre-operative preparations. Despite this, inpatients' health conditions are more variable (e.g., development of a fever), which could sometimes force the postponement of the surgery on the day of surgery [66, 141].

Apart from the scheduled elective patients, there might appear unexpected non-elective patients (for whom a surgery is required on short notice) in the hospital. Furthermore, some researchers classify surgeries into more than two urgency classes by using a surgery target/due time (DT). The due time is a time interval within which it is best for a patient to receive the actual procedure [189]. Thus patients are considered to have health risks if their surgery is performed after their target DT. In the literature, unfortunately, varying surgery DT intervals are used for denoting patients. Moreover, even for a similar DT interval, the used categorization terms are often different, e.g., urgent and high priority.

According to the urgency definition of the National Confidential Enquiry into Patient Outcome and Death (NCEPOD) [137], we classify surgeries into four types: elective, expedited (or scheduled), urgent, and immediate (or emergency). Generally, we consider patients who need to have surgery within 30 days as expedited patients. A surgery is normally considered an urgency if it can be delayed for a short time (i.e., hours), while an emergency if it must be performed immediately. Table 5 classifies the literature based on the four categorizations. For both outpatient and inpatient scheduling problems, a small number of articles distinguish between elective and expedited patients. In addition, the literature on elective and expedited patient scheduling is larger as opposed to its non-elective (i.e., urgent and immediate patients) counterpart.

Table 5: Categorization based on surgical urgency

Category	Inpatient	Outpatient
Elective	[2–9, 11–16, 18–28, 30, 31, 35–38, 40–43, 47–53, 55, 63, 68–70, 74–78, 80, 86–90, 92, 98–103, 105–107, 109–114, 116–128, 130–136, 139, 141–144, 147, 148, 150, 152, 154, 156, 158–162, 164–167, 169, 171–173, 175–183, 185–193, 197, 199–203, 206–209, 212]	[4–6, 8, 10, 12, 15, 16, 18, 19, 22, 24, 29, 33–36, 38, 39, 43–45, 47, 49, 50, 54–56, 58, 61, 63, 65, 68–70, 72, 75, 76, 78, 79, 81, 83, 84, 86, 87, 92, 94, 96, 103, 109, 111, 113–117, 119, 120, 122–128, 132, 133, 135, 136, 138, 143, 144, 149–152, 156–158, 161, 167, 169, 170, 173, 175, 177, 178, 185, 189–192, 194–197, 200–202, 205, 210]
Expedited (scheduled)	[4, 5, 9, 12, 19, 23, 25, 42, 47, 86, 103, 124, 126–128, 133, 152, 154, 167, 185, 189, 192, 203, 204]	[4, 5, 12, 19, 47, 86, 103, 124, 126–128, 133, 152, 167, 185, 189, 192]
Urgent	[15, 16, 26, 36, 48, 74, 86, 130, 141, 144, 154, 158, 192]	[15, 16, 21, 33, 36, 86, 144, 158, 192]
Immediate (emergency)	[2, 15, 16, 22, 25, 36, 37, 43, 75, 76, 86, 88, 101, 102, 105–107, 109, 113, 118, 119, 125, 130, 134, 135, 144, 147, 148, 154, 156, 169, 179, 185, 192, 200–202, 212]	[15, 16, 21, 22, 36, 43, 75, 76, 86, 109, 113, 119, 125, 135, 144, 156, 169, 170, 185, 192, 196, 201, 202]

Notes. Elective: planned. Expedited: normally within days of decision to operate. Urgent: normally within hours of decision to operate. Immediate: normally within minutes of decision to operate.

Compared to the inpatient literature, the outpatient literature less often incorporates the non-elective patients. If the literature is narrowed down to solely involve outpatient surgery, only 3 papers explicitly mention incorporating the non-elective patients in their problem of interest (i.e., Stuart and Kozan [170], Berg and Denton [33], and Wang et al. [196]). The reason might be that outpatient non-electives in general need less urgent surgery than those in an inpatient setting. For example, trauma specialty is often taken into account in the inpatient literature along with other surgical specialties (e.g., [132, 162, 180, 201]). As the trauma specialty usually handles very urgent patients, inpatient surgeries in this context tend to have more variation in terms of the patient demand and of the surgery duration.

3.2. *Surgery duration*

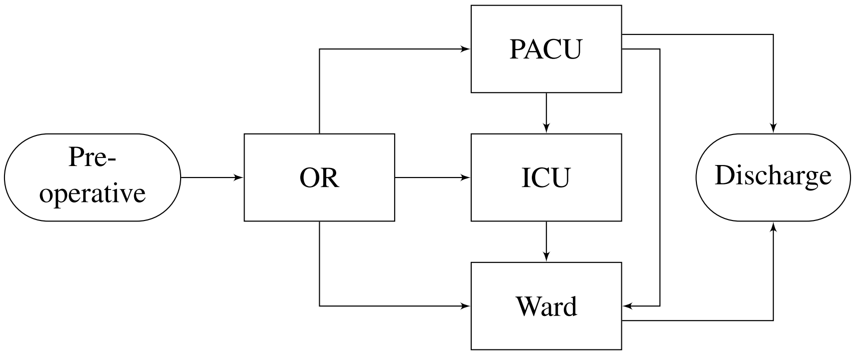
The surgery duration of a patient is normally defined as the time interval between the moment the patient is rolled into the OR and the time when the patient leaves the OR. According to this definition, the turnover (or cleaning) time would not be included into the surgical time. However, there are still many papers incorporating turnover time in the surgery duration (e.g., [20, 109, 125, 208]) for reasons of convenience or of complying with the practice at the case hospital [20]. Estimated surgery durations are typically used at the time of surgery scheduling, but the realized surgery durations are unknown at this moment.

The extent of variability in the surgery durations is usually measured by the standard deviation or the coefficient of variation (CV, i.e., the ratio of the standard deviation to the mean). According to the papers [63, 104, 173], the surgery duration of outpatients tends to be shorter and to have a smaller CV as opposed to that of inpatients. To the extreme, Cardoen et al. [44] assume that surgery durations are deterministic in an outpatient surgical environment. Contrarily, some authors also argue that even for very routine outpatient surgeries, the duration of activities exhibits some uncertainty [32, 84].

It is challenging to predict surgery durations due to the fact that the durations are affected by many complex factors, e.g., the surgery type and the professional ability of the surgeon. In addition, some surgeries do not appear frequently and newer procedures are constantly being developed, and thus the available data are not sufficient to predict their durations [150, 154], which is quite real for inpatient surgery. A large number of papers estimate surgical durations according to historical records and/or predictions of surgeons. The authors in general first make an effort to fit a theoretical statistical distribution to the data collected on surgery durations. Table 4 shows that by far the most frequently used distribution of the surgery duration for both inpatients and outpatients is the lognormal distribution. When no statistical evidence was obtained, the empirical distribution (i.e., an empirical measure of data) is fitted for the data available, which is the second most popular distribution in the literature. Moreover, some authors use machine learning methods to obtain better estimates of surgery durations [79, 141]. More recently, some authors use uncertainty sets instead of the probability distribution to handle the variable surgery duration [22, 124, 150]. Because the estimation of surgery durations exceeds the scope of this article, we will not delve more deeply into this topic.

3.3. *Length of stay*

In addition to patient demand and surgery durations, the stochastic LOS in the downstream units (e.g., the post-anesthesia care unit (PACU), the ward bed, and the intensive care unit (ICU), see Figure 3) is often considered in the integrated OR planning and scheduling for both inpatient and outpatient settings. The LOS is an amount of time during which operated patients occupy a recovery unit in order to recover following the surgery. In Table 3, the patients' LOS of both settings must be read with caution. On an inpatient basis, the LOS (longer than one day) in the ward bed/ICU is often considered. In contrast, outpatients are expected to go home on the day of surgery and the LOS often means the time in the PACU. This is a major bottleneck for the outpatients [84, 151, 157]. The patient LOS differs per surgery type/group. This is why many papers estimate the distribution of the LOS for each surgery type/group (e.g., [23, 31, 84, 92, 160, 192]). The variable LOS of patients will bring deviations of the real bed demand from the assigned capacity, which sometimes results in a congested downstream unit. This adverse impact can be partly mitigated by building balanced master surgery schedules (MSSs) that consider a stochastic LOS [27, 76, 77].



Notes. OR: operating room; PACU: post-anesthesia care unit; ICU: intensive care unit.

Figure 3: Main patient flows for a surgical patient

Table 6 provides a classification of the articles by the different resources (e.g., PACU, ward, and ICU) considered, along with the operating theatre focus. Moreover, it distinguishes between the inpatient and the outpatient setting. We find that 56% of the reviewed papers incorporate some of these resources in OR planning and scheduling in order to improve their combined performance.

3.4. Other uncertainty

Other uncertainty that is considered in OR planning and scheduling includes stochastic OR turnover times, i.e., the time between successive surgeries of the OR (e.g., [69, 74, 141]), uncertainty in pre-operative activities (e.g., [68, 84, 157, 190]), uncertainty in the staff availability (e.g., busy doctors [68]), etc. Part of this uncertainty is taken into account in both settings, whereas part of it is only incorporated in either the inpatient setting or the outpatient setting.

Even though the inpatients and the outpatients experience the surgical services in a similar fashion in the hospital, the characteristics of many specific activities for them are substantially different. The inpatient surgery process encounters a higher unpredictability of those aforementioned surgical activities (e.g., the arrivals of emergency patients, the surgery durations, and the LOS), which would result in a challenging OR planning and scheduling problem.

Table 6: Classification based on the resources conisdered

		Inpatient setting	Outpatient setting
Isolated OR		[4, 5, 7, 11, 14, 19, 21, 22, 31, 47, 51, 52, 55, 63, 70, 78, 86, 89, 90, 98, 105, 106, 109, 111, 112, 114, 116, 119, 120, 123–128, 130, 133, 136, 142, 143, 147, 148, 150, 152, 154, 159, 161, 167, 173, 177, 179, 180, 182, 183, 188–190, 192, 202, 206–209]	[4, 5, 10, 19, 22, 33, 34, 39, 47, 54, 55, 63, 65, 70, 78, 79, 81, 83, 86, 109, 111, 114–116, 119, 120, 123–128, 133, 136, 138, 143, 150, 152, 161, 167, 170, 173, 177, 189, 190, 192, 194, 196, 202, 205, 210]
Integrated OR	PACU	[6, 15, 16, 18, 20, 40, 49, 50, 68, 69, 87, 99, 113, 122, 131, 132, 135, 144, 165, 169, 175, 181, 191, 197]	[6, 15, 16, 18, 29, 44, 45, 49, 50, 56, 68, 69, 72, 84, 87, 94, 96, 113, 122, 135, 144, 149, 151, 157, 169, 175, 191, 195, 197]
	Ward	[2, 3, 6, 12, 13, 15, 16, 23–28, 30, 35–38, 41–43, 48, 50, 53, 74–77, 80, 87, 88, 100, 102, 103, 107, 117, 118, 121, 131, 132, 134, 135, 141, 144, 156, 160, 162, 164–166, 171, 172, 175, 176, 178, 185–187, 191, 193, 199–201, 212]	[15, 16, 38, 43, 50, 58, 61, 76, 103, 132, 144, 191]
	ICU	[2, 3, 9, 12, 15, 16, 25, 37, 50, 53, 75–77, 88, 92, 99–102, 107, 110, 132, 134, 135, 139, 144, 156, 158, 160, 171, 172, 175, 193, 203, 204]	[58, 61, 76, 92, 158]
	Other	[8, 13, 15, 16, 18, 49, 68, 87, 99, 117, 122, 144, 175, 185, 197, 212]	[8, 15, 16, 18, 29, 49, 56, 68, 84, 87, 96, 117, 122, 144, 149, 157, 175, 185, 197]

4. Research methodology

A large body of literature tries to improve the performance of OR planning and scheduling by using various methods at different decision levels. In Section 4.1, we introduce four classical decision levels. Next, specific research methodologies in the literature are classified and discussed in Section 4.2.

4.1. Four hierarchical decision levels

According to the time frame, OR planning and scheduling in hospitals can be classified into four different hierarchical decision levels: strategic, tactical, offline operational, and online operational [91]. The strategic level addresses the dimensioning of OR time among different surgical groups (often referred to as case mix planning), typically with a long-term planning horizon (e.g., a year or more). The tactical planning level assigns the OR time to surgeons or surgical groups over a medium term (e.g., several weeks). This level usually generates so-called MSSs which define the number, type, and opening hours of available ORs, as well as the allocation of OR time among surgical groups. The offline operational level usually deals with patient-to-date scheduling decisions and surgery sequencing problems for elective patients. Last, the online operational level handles the monitoring and control of the process during OR schedule execution.

4.2. *Research methodology classification*

It is evident that making these decisions is not a simple task and here the proper research methodologies are capable of making a difference. Table 7 classifies the literature according to the applied methodologies. Figure 4 further shows the number of papers according to the decision levels and the patient types. As can be seen, the offline operational level is most studied in both settings (inpatient and outpatient) in the reviewed literature. At all decision levels, the number of papers in an outpatient setting is smaller than that in an inpatient setting. One would expect there to be different methodological focuses in the outpatient and the inpatient settings. However, Figure 4 reveals that at each decision level, both settings observe a similar share of different methodologies applied. Therefore, in the following, we do not distinguish the two settings when we discuss the methodologies.

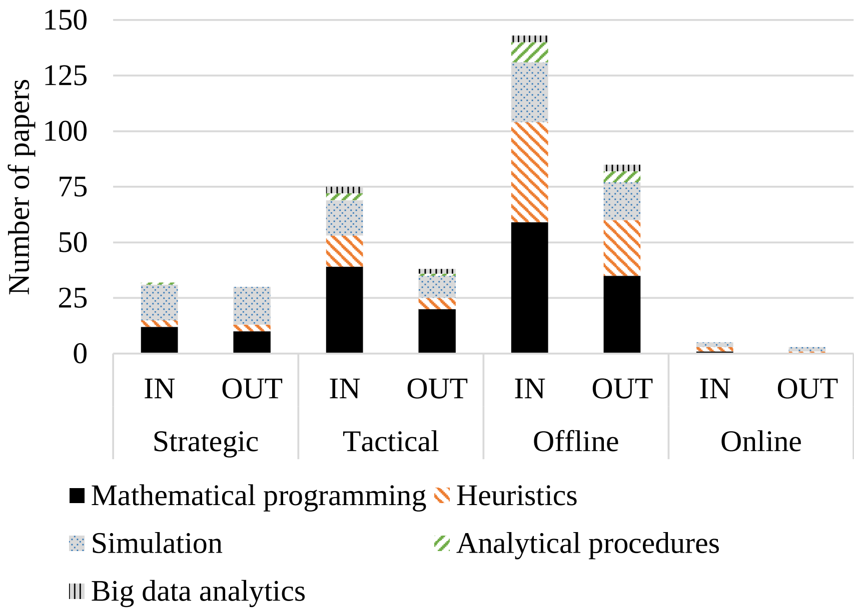


Figure 4: Methodologies considered at each decision level (IN: inpatients and OUT: outpatients)

Mathematical programming (e.g., mixed integer programming (MIP)) models are shown to be used the most overall, especially at the tactical and offline operational levels. In this type of methodology, the OR planning and scheduling problem is normally represented in mathematical terms, which seeks to maximize or minimize the objective. It is subject to a set of mathematical constraints that portray the conditions under which the decisions have to be made. These models can then be solved by using standard software (e.g., CPLEX solver [12, 87]) or by developing exact solution methods (e.g., branch-and-price [121, 138]).

In order to incorporate some sort of uncertainty, the stochastic programming counterparts of the mathematical models are increasingly used in the literature (e.g., stochastic integer programming [33, 132] and stochastic MIP [100, 150]). Stochastic programming models usually optimize some objective function in expectation and assume that probability distributions of the underlying stochastic parameters are known. However, true distributions may not be available in reality, which will result in unreliable solutions. Alternatively, robust optimization optimizes for the worst case in an uncertainty set of the stochastic parameters, usually without requiring full knowledge about their probabilistic distributions. Furthermore, computational speed and tractability are also a reason why the recent literature begins to use such methodology [22, 124, 134, 150]. However, robust optimization tries to hedge against all possible worst-case realizations of the stochastic parameters, which results in highly conservative solutions in some cases. For example, if the buffer capacity decision is made to be too conservative by this methodology, then the number of served elective patients will be affected. In order to deal with the issues of the above two methodologies, a recent research by Deng et al. [54] develops a distributionally robust optimization model. This model can seek the worst-case distribution over an ambiguity set describing available distributional information of random parameters (i.e., surgery durations).

Heuristics are often thought of as a useful approach to solve OR planning and scheduling problems, including constructive heuristics, improvement heuristics, meta-heuristics, heuristics based on exact methods (e.g., column generation based heuristics), etc. Heuristics are relatively easy to implement, but cannot guarantee a global optimal solution. Constructive heuristics (e.g., the longest processing time first [84]) may be done by adding one item at a time to a partial solution, while meta-heuristics (e.g., genetic algorithm [89], tabu search [14], and simulated annealing [48]) alternates between diversification and local search to identify better solutions. Table 7 indicates that the meta-heuristics are the most popular heuristics. One reason is that the meta-heuristics are widely used for solving the mathematical models in the literature (e.g., [14, 77, 157, 167]). When testing on real data, the computational results have shown that the heuristics work fairly well compared to the exact solution methods within a reasonable time limit. Among other heuristics, we find that sample average approximation is increasingly used to approximately solve stochastic models [100, 101, 105, 132]. This method allows for finding a good solution among a limited number of scenarios.

Simulation is used at various decision levels mainly to perform two roles: (1) scenario analysis and (2) evaluation of model solutions. The former is to compare multiple scenarios, policies, and changes to the OR setting in terms of PMs of interest. For example, at the strategic decision level, Dexter et al. [63] apply discrete-event simulation (DES) to test the impact of increasing patient volume on revenue and OR utilization at the surgical suite. Freeman et al. [74] use simulation to evaluate each candidate case mix plan with respect to various performance measures so that the decision makers can make a selection among those plans. At the tactical level, van der Kooij et al. [177] develop a generic DES framework to evaluate the scheduling of ORs with a releasing mechanism (i.e., determining when OR time is made available for scheduling elective patients of all specialties). At the offline operational level, Samudra et al. [154] create a DES model by incorporating many realistic aspects of the surgery setting of our case hospital, in order to test various patient scheduling policies. Simulation is versatile in its account of the complex as well as stochastic nature of the OR setting and in accounting for multiple different PMs. The negative sides of this technique are that the development of a precise simulation model might be time-consuming and that it is hard to obtain optimal solutions by this technique.

The second role of simulation is normally combined with mathematical programming models and/or heuristics (called simulation-optimization). Some papers first tailor deterministic optimization models that are used to produce possible solutions, and then these solutions are evaluated under uncertainty by simulation models (e.g., [20, 23, 36]). For a similar purpose, heuristics are also combined with simulation to assess and search for a better solution [68, 84, 157]. These are common at the tactical and offline operational levels where the MSS and the surgery schedule are optimized, respectively. The advantage of simulation-optimization lies in allowing to solve complex optimization problems by using an optimization model, while including various features surrounding the OR planning and scheduling problem by simulation.

Apart from the aforementioned methodologies, analytical procedures such as Markov Decision Processes [25, 118] and queueing theory [80, 162] have also been used in the uncertain OR planning and scheduling context. Analytical approaches can model the patient flow by stochastic processes and generate exact/analytical results that are unattainable with other methodologies. Nonetheless, they require many simplifying assumptions, e.g., often assuming exponentially distributed service times and unlimited waiting space in the queueing model. This disadvantage might reduce the flexibility of analytical approaches and make models more difficult to solve for some complex OR processes.

On top of traditional operations research methodologies, big data analytics (BDA) are attracting attention from researchers in the field of OR planning and scheduling, e.g., machine learning and data mining, in recent years. Big data analytics are normally used for analysis on large-scale datasets called ‘big data’ and for functions of classification, association, clustering, as well as optimization [140]. Papers of OR planning and scheduling use BDA for different purposes, including grouping similar surgeries [12, 160], predicting the duration of key activities (e.g., surgery durations [79, 141], PACU LOSs [69]), and predicting the PMs of interest (e.g., the probability of surgical cancellations [119] and the bed occupancy in the ICU [158]). These outcomes of BDA are then incorporated as inputs of the traditional operations research models or used as a supporting tool for decision makers.

In short, there is no apparent trend on which methodologies are more popular in which setting (inpatient and outpatient). However, when we look at different decision levels separately, simulation can be applied for dealing with problems at different decision levels. At lower-level decisions (e.g., the tactical and the offline operational level), mathematical programming is most used, in which stochastic programming and robust optimization seem to be able to effectively incorporate stochasticity. Moreover, the combinations of different methodologies (e.g., simulation-optimization and distributionally robust optimization) are promising to account for optimality, complexity and stochasticity in the OR planning and scheduling problem.

Table 7: Overview of methodologies considered

Methodologies	References
Mathematical programming[1]	
Linear programming	[58, 61, 111, 135, 208]
Goal programming	[2, 3, 35, 42, 53, 116]
Integer programming	[19, 28, 31, 33, 44, 65, 69, 79, 98, 107, 121, 132, 152, 157, 171, 172, 178, 196, 209]
Mixed integer programming	[4, 6–9, 12, 14, 20, 21, 23, 24, 27, 30, 34, 41, 45, 50, 52, 54, 55, 74, 75, 78, 83, 87–89, 99, 100, 102, 105, 106, 109, 110, 112, 113, 121, 124–126, 130, 133, 134, 138, 139, 141–144, 147, 150, 156, 160, 165, 167, 175, 176, 179, 181, 183, 188, 191–193, 195, 199, 201, 204, 206, 210]
Quadratic programming	[27, 30, 41, 92]
Chance-constrained	[54, 101, 105, 188]
Exact solution methods	
Column generation	[7, 106, 139, 196, 204]
Dynamic programming	[25, 28, 45, 120, 196, 203]
Branch-and-bound	[33, 44, 77, 170, 193]
Branch-and-price	[28, 45, 121, 138, 206]
Branch-and-cut	[54, 209]
Heuristics	
Constructive heuristics	[11, 14, 49, 55, 90, 96, 113, 123, 127, 128, 133, 134, 165, 175, 179, 182]
Improvement heuristics	[7, 77, 126–128, 133, 167]
Meta-heuristics	
Genetic algorithm	[51, 68, 84, 89, 113, 117, 123, 127, 158, 164–166, 175]
Simulated annealing	[11, 27, 30, 48, 56, 77, 88, 90, 133, 160, 167, 178, 179]
Tabu search	[14, 94, 112, 157, 176, 179]
Others	[7, 11, 14, 21, 55, 68, 89, 90, 112, 133, 134, 136, 159, 164–166, 188, 197, 209]
Heuristics on exact methods	[7, 25, 27, 106, 109, 133, 196, 204]
Other heuristics	[5, 20, 25, 34, 40, 101, 105, 120, 132, 150, 171, 179, 188, 190, 203, 204, 209]
Simulation	
Discrete-event simulation	[2, 10, 13, 15, 16, 18, 20, 23, 24, 34, 36–39, 41, 43, 49, 53, 63, 68–70, 72, 74, 84, 86, 88, 92, 96, 103, 107, 110, 114, 117–119, 121, 122, 130, 131, 141, 148, 149, 151, 154, 157, 169, 173, 177, 179, 183, 185, 188, 190, 192, 200, 201]
Monte Carlo simulation	[6, 50, 56, 61, 101, 109, 112, 176]
Analytical procedures	
Markov decision processes	[25, 52, 118, 161, 202, 203, 212]
Queueing theory	[80, 162]
Others	[26, 34, 76, 77, 114, 194]
Big data analytics[2]	[12, 69, 79, 119, 141, 158, 160]

Notes. 1: Some papers develop deterministic optimization models, while some papers incorporate uncertainty into their models using e.g., stochastic programming and robust optimization. 2: Big data analytics include machine learning and data mining, etc.

5. PM comparison of inpatient and outpatient

In order to obtain practical implications about the difference in the scheduling performance between an outpatient setting and an inpatient setting, in this section, we only consider papers in the classification scheme that use real data in their testing or application phase of the involved methodologies. Section 5.1 discusses the articles that explicitly or implicitly compare the performance of surgery scheduling between both settings, while Section 5.2 collects the statistics of their performance results from the related papers.

5.1. PM comparison of inpatient and outpatient (Paper-to-paper description)

Even though a considerable number of articles have been written on OR planning and scheduling, very few articles directly or indirectly investigate the relative performance of surgery scheduling between the two settings. Only eleven related articles are identified (see Table 8) and will be discussed in the following.

Dexter et al. [63] investigate the impact on revenue and OR utilization of increasing the volume of patients for both the inpatient hospital suite and the ASC with a relatively high OR utilization (90%). It is illustrated that increasing the patient volume (by the amount expected to 'fill' the OR) just results in slight improvements in utilization instead of 100% utilization for both settings, with a smaller increase in the inpatient ORs (by <1%) than in the ASC (4%). Through a sensitivity analysis, they explain that the smaller increase for the inpatient surgical suite is due to fewer patients to schedule (so that the variability in patient arrivals has a larger effect) and a poorer 'packing' of the longer inpatient surgery durations into each OR. In terms of the revenue, the increase in patient volume may increase the profitability for the ASC (by 1.8%), while there is a decrease for the inpatient hospital (by 0.7%). The decrease of the revenue is because the additional patients might displace other more lucrative patients from OR time as a result of the poorer 'packing' in the inpatient setting. Thus, scheduling inpatient surgeries is inherently different from outpatient OR planning and scheduling.

For simulating the effects of opening the ASC, Tyler et al. [173] move healthier patients to this center and then sicker inpatients (whose case times are normally longer and more variable) are left in the main hospital. However, their results need to be considered with caution. Even though the main hospital appears to achieve a higher utilization after outpatients are removed (from 89% to 97%), the OR overtime and the patient waiting time on the day of surgery increase to 15.3 and 24.7 minutes, respectively. The two results are beyond the operational goals set in their research (15 minutes for both). This is because the larger duration variance in the remaining heavier surgeries leads to the difficulty to achieve a better trade-off between a higher utilization and a shorter OR overtime as well as a shorter patient waiting time. By comparison, the ASC is able to perform all the cases within an acceptable overtime and patient waiting time (i.e., 0.1 and 3.6 minutes).

Similarly, Bowers and Mould [38] examine the impact of the separation of elective ambulatory patients and inpatients on the hospital ward, on the profile of surgery activities, and on the operating theater utilization. First, they show that the utilization in the ambulatory care ORs is always better than the utilization of the inpatient ORs for each separation definition of ambulatory care. The reason is that the introduction

Table 8: Papers related to a performance comparison between outpatients and inpatients

Authors (year)	General Information		Problems addressed	Method	Comparison results	
	Country	Hospital			Outpatient	Inpatient
Dexter et al. (2001) [63]	USA	A University hospital	Study the impact of increasing patient volume on utilization and revenue for the inpatient hospital suite and ASC.	DES	Utilization, Profitability	
Tyler et al. (2003) [173]	USA	Children's Hospital of Philadelphia	Study the impact of moving healthier patients to ASC from the main hospital (left with sicker patients).	DES	Direct wait, Overtime	Utilization
Bowers and Mould (2005) [38]	UK	Scottish District General Hospital	Study the impact of the separation of day-care patients and inpatients on wards, on OT activity profile and on utilization.	DES	Utilization	
Zhang et al. (2009) [201]	USA	Los Angeles County General Hospital	Improve the OR capacity allocation among specialties to minimize inpatients' LOS before surgery.	MIP, DES	Indirect wait	
Gupta et al. (2007) [86]	Canada	A regional cardiac center	Improve capacity planning regarding patient waiting times for urgent inpatients, urgent outpatients, and elective outpatients.	DES		Indirect wait
Vansteenkiste et al. (2012) [189]	Belgium	A University hospital	Define a method to reallocate OR capacity between and within surgical disciplines based on patients' DT deviation.	Statistical analysis	Within DT	
Xue et al. (2013) [198]	USA	A University hospital	Study surgery cancellations for inpatients and outpatients at a university hospital.	Statistical analysis	Cancellation	
Dexter et al. (2014) [64]	USA	21 nonacademic facilities and 1 academic hospital	Study relative effect on total canceled OR time from patients who are inpatients or outpatients preoperatively.	Statistical analysis	Cancellation	
Luo et al. (2018) [119]	China	University hospital	Seek optimal surgery scheduling strategies by considering cancellation prediction and nonelective surgeries.	Data mining, DES	Cancellation	
Kadhim et al. (2016) [104]	USA	Children's Hospital Philadelphia	Study the differences in surgery times and OR work efficiency between inpatient and outpatient facilities in the same hospital.	Statistical analysis	OR efficiency	
Aissaoui et al. (2020) [6]	Tunisia	A private clinic	Improve the stability and robustness of surgery scheduling considering late surgery start or delay disruptions.	MIP, Monte Carlo simulation	Direct wait	

Notes. Method: DES (Discrete-event simulation); MIP (mixed integer programming). PMs: Indirect wait (patient waiting time to be scheduled); Direct wait (patient waiting time on the day of surgery); Within DT (the percentage of patients served within their target DT); OR efficiency (the percentage of work completed before mid-day). The shown PM under a setting represents that the PM result is better in that setting.

of an ambulatory care center causes the profile of the surgery activities in the main hospital to change with relatively more long surgeries which are difficult to fill a half-day OR session. Fortunately in their case, the issue could be overcome through adopting full-day OR sessions. Second, the decline in the overall bed requirement is not proportional to the increase in the proportion of the ambulatory patients, which is caused by the fact that a lot of beds are used by patients with a longer LOS.

The difference in patient waiting times for surgery between inpatients and outpatients can be discerned in the study of Zhang et al. [201]. The authors aim to minimize inpatients' LOS in the hospital before surgery by an MIP model. They also incorporate the outpatients' waiting as an objective element since the outpatients indirectly affect the inpatients' waiting by competing for OR capacity. Both the actual hospital data and the best solution produced by the MIP model result in the waiting days of inpatients for surgery (1.86 and 1.54 days, respectively) to be longer than that of outpatients (0.34 and 0.33 days, respectively). A major cause is that outpatients are given a higher priority over inpatients in the authors' case hospital (scheduling preference). Moreover, in the sensitivity analysis with an increase in the patient demand, the difference between both patient types is still the case (even larger). This means that the waiting time of inpatients is more sensitive to the growing demand for surgery in this hospital.

Despite the great performance of the outpatient setting, there exists research that produces different results. Gupta et al. [86] optimize OR capacity planning via computer simulation in order to reduce patient waiting times (to be scheduled) in a regional cardiac center, where patients are classified into three types, i.e., hospitalized urgent patients, urgent outpatients, and elective outpatients. When comparing their waiting times, the hospitalized urgent patients have the least (1.6 days), while the latter two patient types suffer a longer waiting (7.4 and 15.9 days, respectively). The result seems conflicting with most of the aforementioned research. This is caused by their case hospital recommending different target waiting times for each type of patients (and the hospitalized urgent patients are given the highest priority). This indicates that the patients' medical urgency plays an important role in their waiting time results.

In addition to regular PMs, the due time related PMs are compared in an inpatient and an outpatient OR setting based on historical data of a University hospital in the study of Vansteenkiste et al. [189]. The authors' data reveal that all three care programs of a specialty (i.e., gynecologic specialty) in the outpatient setting consistently have a higher percentage of surgeries performed within their DT (called within DT percentage) than those in the inpatient setting. This is due to the fact that the smaller and more predictable surgeries are served in the outpatient ORs of the authors' case hospital, and the outpatients are thus treated in a quite efficient way.

At the hospital, reducing the number of cancellations is a key issue due to the fact that cancellations disrupt the OR schedule, decrease the quality of surgery service, and create an additional workload to the scheduling office (e.g., rescheduling decisions and communication with patients). In the literature, the term cancellation can include actions where surgeries are removed from the OR schedule already before the day of surgery or on the day of surgery. Based on the former definition, Dexter et al. [64] analyze the cancellation data in both nonacademic and academic hospitals, and differentiate inpatients and outpatients. They conclude that in both types of hospitals, inpatients account for approximately 50% and 70% of the total canceled minutes although they only represent about 16% and 22% of the total scheduled minutes of surgery, respectively. They explain that more than half the total inpatient canceled minutes (54%) are caused by patients who are scheduled within 1 workday before the day of surgery. Based on the latter definition of cancellation, Xue et al. [198] report that the cancellation rate (18.1%) of inpatients is much higher than that of outpatients (4.6%). The higher cancellation rate is mainly associated with inadequate preoperative preparation. A similar result about the cancellation difference between both patient types is also obtained in Luo et al. [119] who reveal that the cancellation rates for elective inpatient surgery and for day-care surgery are 15.8% and 5.1%, respectively. The authors indicate that the reasons for cancellation include the difficulty in performing a surgery, the surgery duration, and the involved surgical procedure, etc. Therefore, it seems that inpatients might suffer a higher cancellation rate.

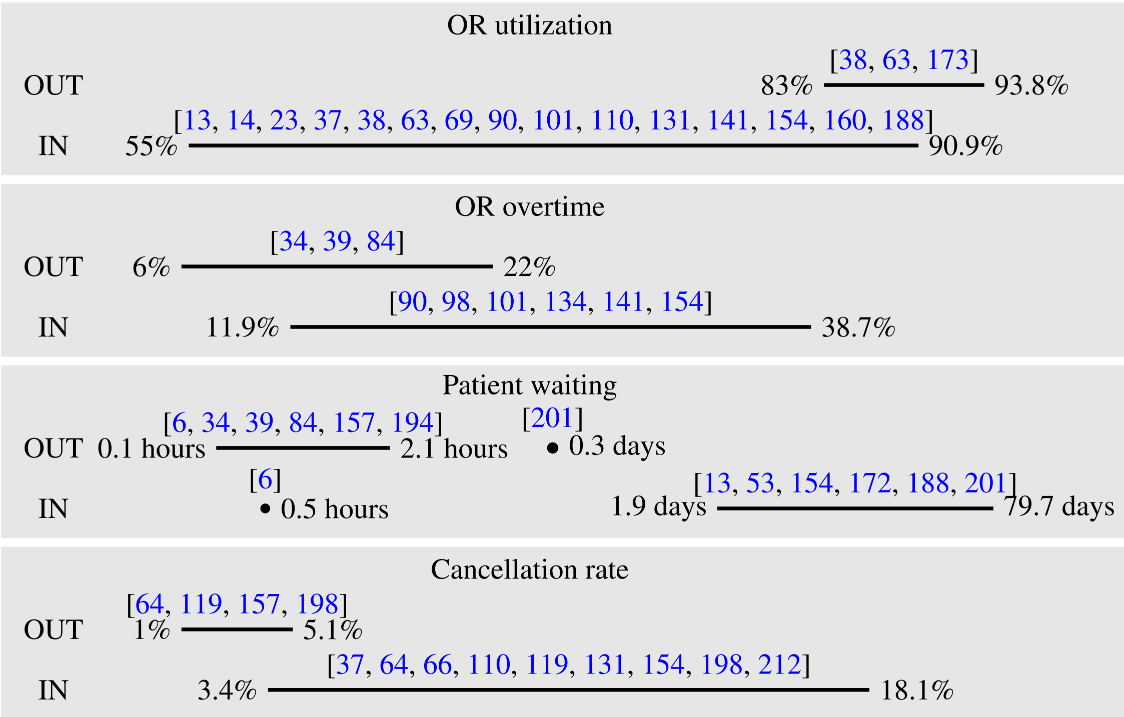
In a statistical way, Kadhim et al. [104] study the differences in the orthopaedic surgical time and OR work efficiency (i.e., the percentage of work done before mid-day) between inpatient and outpatient surgery facilities in the same hospital. The OR efficiency at the hospital-owned ASC (72.5%) is higher than in the inpatient hospital (49.5%) despite the common variables of the same surgeon performing the same procedure. The authors explain that the work time at the outpatient facility is often predictable, which is not the case for the inpatient hospital where the procedure time is less predictable and longer on average. Similarly, the USA national survey of ambulatory surgery cases reports that 64% of the OR case time is complete before noon and 90% before 3 p.m. [59].

In the study of Aissaoui et al. [6] for a private clinic, inpatients and outpatients are shown to have a different degree of surgery delay on the day of surgery. Specifically, the inpatients have a longer average delay (30 minutes) than outpatients (15 minutes) based on real-world data in their study. One reason is that the private clinic prefers to serve outpatients, who have day-care surgery, early in the morning so that these patients are less likely to spend the night in the hospital for post-operative care.

Overall, the eleven papers in Table 8 reveal that outpatient surgery can be performed in a more efficient way as opposed to inpatient surgery although hospitals are different in terms of the country and the type. Important insights include: (1) the shorter duration and the lower variability in outpatient surgery facilitate a better performance of surgery scheduling; (2) the patient waiting time to be scheduled is mostly affected by the patients' medical urgency and the hospital scheduling preference; (3) there is a competing relationship among some PMs, e.g., OR utilization, OR overtime, and surgery delay on the day of surgery.

5.2. PM statistics for inpatient and outpatient settings

In this section, we collect the statistics of the performance results of both settings from the related papers. As can be seen from Figure 5, the OR utilization is different between an inpatient surgical setting and an outpatient surgical setting. The utilization of inpatient ORs roughly ranges from 55% to 90.9% and this range depends on many factors, such as the case mix, the case hospital, and the scheduling approaches. Contrarily, the outpatient-related literature shows that the OR utilization varies in the interval between 83% and 93.8%. This indicates that outpatient ORs are usually able to be more utilized than inpatient ORs.



Notes. OUT: outpatients, IN: inpatients. As for patient waiting, the unit of hours relates to the direct waiting time (on the day of surgery), while the unit of days implies indirect waiting time (to be scheduled). The cancellation rate is calculated as dividing the number of canceled surgeries by the number of scheduled surgeries.

Figure 5: Statistical results of PMs for outpatients and inpatients in the literature

With regards to the OR overtime (which is represented as a ratio of the amount of overtime to the regular OR opening time), it is higher for an inpatient setting compared to that of an outpatient setting as a whole. For instance, Ozen et al. [141] aim to improve the OR performance of orthopedic spine surgery practice (inpatient setting) at the Mayo Clinic which normally serves lengthy (mean time of 4 hours) and highly variable spine surgeries. Their results show that the overtime is still above 20% although it was reduced already after the authors have performed an improved scheduling method (originally 38.7%). Other results for an inpatient setting also show a relatively high OR overtime, e.g., 13.6% in Samudra et al. [154] and 25.3% in Moosavi and Ebrahimnejad [134]. On the contrary, the outpatient procedure center in Berg et al. [34] demonstrates an average overtime of 6%-20% for different test instances. Gul et al. [84] reports the overtime results for different configurations of surgical cases in an outpatient setting, which range from 1 to 2 hours (i.e., 11%-22%). However, in their study, the overtime is defined as the difference between the time the last patient leaves the recovery room (instead of the operating room) and a regular closing time. This is also the case in Burns et al. [39] with a reported average overtime of 10%. Ozen et al. [141] give a reason for the higher inpatient OR overtime: emergency surgery due to infections. In this regard, outpatient surgery has a lower risk of infections as they often consist of standardized procedures and are separated from sicker inpatients.

The patient waiting time is usually classified into two types: direct waiting time and indirect waiting time. Direct waiting time is the surgery delay of patients on the day of surgery. Indirect waiting time refers to the patient waiting to be scheduled on a given day for elective surgery, which is normally measured in days. The focus of patient waiting time in the related literature is different for inpatients and outpatients. The indirect waiting time is frequently used in the inpatient setting. The waiting length could vary considerably from article to article, as displayed in Figure 5 (e.g., 1.9 days in Zhang et al. [201], 2.5-25.1 days in Dellaert and Jeunet [53], 38.2 days in Samudra et al. [154], 7.6-79.7 days in Testi and Tànfani [172]). Only Aissaoui et al. [6] report on direct waiting time (0.5 hours) for inpatients. Differently, most of the outpatient papers focus on the direct waiting time [6, 34, 39, 84, 157, 194], except Zhang et al. [201] who report on the indirect waiting time. The reason why the direct waiting time is less studied in the inpatient setting is that elective surgical cases are usually admitted as inpatients some days ahead of surgery and that the waiting time after their admission is mostly due to necessary pre-operative preparations. This reflects, to some extent, that the indirect waiting time closely relates to the inpatients' satisfaction.

As for the cancellation rate, it can be defined based on either surgery counts or canceled times in the reviewed studies, in which we find the former definition commonly being used. That is, the cancellation rate is mostly computed as the numerical counts of canceled surgeries divided by the number of scheduled surgeries. Figure 5 shows that it is possible to achieve a lower outpatient cancellation rate at different hospitals, e.g., $\leq 2\%$ among non-academic hospitals [64, 157], and 4.6% to 5.1% at academic hospitals [119, 198]. On the contrary, cancellation rates are relatively higher among inpatients, e.g., 8.1% to 14.1% among non-academic hospitals [37, 64, 131], 11.8% to 18.1% among academic hospitals [66, 198, 212]. However, Samudra et al. [154] report a cancellation rate of 3.4% at the University Hospital Leuven's inpatient surgical department. This number seems very small because the case hospital is more reluctant to cancel a surgery, but rather reassigns it to another OR on the day of surgery if possible. In addition, it has more allowance for overtime. Reasons for cancellations vary across studies and are also different for inpatients and outpatients, including unfitness for surgery (e.g., variable patient medical condition) [66, 141, 168], priority surgery (e.g., emergency arrivals) [37, 119, 168], no-show [168, 198], scheduling issues (e.g., overbooking) [198], etc. Although no-shows are not common for inpatients, their variable medical condition might force them to be canceled. This together with other reasons (e.g., emergency surgery) might lead to a higher cancellation rate among inpatients.

Furthermore, some other PMs show up in the reviewed literature for both OR settings, such as the OR idle time [98], the OR undertime [154], the within DT percentage [154, 189] and the patient throughput [201]. However, the number of papers for each of these PMs is too small to reflect differences between the two settings.

Certainly, different PMs are given different emphasis from article to article. However, by combining Table 8 and Figure 5, there is evidence that outpatient surgery scheduling can be more efficient and effective than inpatient surgery scheduling in terms of most of the PMs, including the OR utilization, the OR overtime, and the surgery cancellation. This is caused by different features between both settings, which can be summarized as follows: (1) outpatient surgery often involves the more standardized procedures with a lower variance and mean in surgery durations, while inpatient surgery is longer and less predictable, (2) although the outpatients' actual arrival time is uncertain with a possible no-show, the emergency arrivals and the variable medical conditions of inpatients might lead to a higher inefficiency, (3) the inpatients are more concerned with the scheduled surgery date, whereas the direct waiting time on the day of surgery is a main issue in the current outpatient surgery scheduling.

6. Discussion and future research

Based on the literature review, we identify future research directions that provide opportunities for expanding existing methodologies and for narrowing the gap between theory and practice. Specifically, we suggest directions for future research in terms of (1) outpatient surgery scheduling (Section 6.1), (2) methodologies and decision levels (Section 6.2), and (3) inpatient surgery scheduling (Section 6.3).

6.1. Outpatient surgery scheduling

There is a need for a more realistic representation of uncertain patterns in outpatient surgery scheduling, e.g., no-shows and non-elective patients. For example, although many papers assume that patients are punctual to their appointments, the patient no-show is common in practice in an outpatient surgical setting (with a no-show probability of 5% to 24% [34, 38, 39, 68, 201]). As a result, inefficiencies, access problems, and cost issues of the surgery delivery will be caused (e.g., the surgeon will become idle and cannot perform another surgery) [34, 38]. In addition, the arrivals of non-elective (urgent or emergent) surgeries often disrupt the elective surgery schedule, but the outpatient literature rarely incorporates the non-elective patients (see Section 3.1). It would be important that future research can incorporate these uncertainties and devise effective interventions to reduce their effect. However, handling both no-shows and non-electives is a very difficult challenge. This is due to the fact that a patient is not considered as a no-show until some time past the planned time point and that non-electives occur randomly [33]. There has been a significant amount of research on appointment scheduling in outpatient clinics for dealing with no-shows (e.g., [108]), but in most of the research patient schedules are created based on fixed appointment slots, neglecting the fact that the surgery durations are more variable. Therefore, outpatient surgery scheduling requires fundamentally different solutions than outpatient appointment scheduling with regards to these topics.

Due to the increasing popularity of outpatient surgery in reality, the outpatient facilities are facing a growing patient demand [17, 73, 174]. As a result, patients might wait for their surgery for longer days (i.e., indirect waiting time to be scheduled). Nonetheless, the literature review shows that most of the current outpatient papers focus on the direct waiting time (i.e., the surgery delay of patients on the day of surgery) (see Section 5.2). For future research, the indirect patient waiting time in the scheduling of outpatient surgery needs more attention in order to perform better patient-to-date scheduling. However, modeling indirect waiting time is challenging for various reasons. Firstly, unlike direct waiting time for which the end of the day is a natural termination of the scheduling horizon, indirect waiting time is more realistically an infinite-horizon problem. Secondly, the scheduling decisions on which day the surgeries will take place need to consider multiple stakeholders' preferences, e.g., the patients and the surgeons. It would be valuable to develop advanced models that solve these problems and that even consider both kinds of patient waiting times together.

6.2. *Methodologies and decision levels*

Researchers need to be cautious in what research methodologies to apply because these methodologies are more or less related to the decision level and the complexity of the scheduling problem. Simulation (i.e., DES and Monte Carlo simulation) can be applied at different decision levels for different purposes, e.g., scenario analysis and testing model solutions. When lower-level decisions (e.g., tactical and offline operational level) have to be solved (sub-)optimally, mathematical programming is most used. In order to solve real-life problems with uncertain patterns, stochastic programming and robust optimization are useful as they are able to effectively incorporate stochasticity. Furthermore, the combinations of different methodologies (e.g., simulation-optimization and distributionally robust optimization) are interesting to study since the advantages of different methodologies can be integrated in order to better solve various OR planning and scheduling problems. In addition, big data analytics (i.e., machine learning and data mining) can provide an enhanced capability for the traditional operations research methodologies not only to increase the accuracy of operations research model inputs (e.g., surgery duration), but also to predict the performance of the model outputs (e.g., the impact of surgery decisions on downstream units). Research on the intersection of the two disciplines constitutes a future field. This is noteworthy due to the advance in hospital information systems from which much data can be stored and extracted.

Furthermore, the integration of multiple decision levels can be another interesting field. One example that integrates the tactical level and the offline operational level is to assign surgery groups, which are clusters of surgery types sharing comparable characteristics (e.g., discipline and surgery duration), to OR blocks. The aim is to create a master surgery schedule that guides the lower-level scheduling decisions, i.e., where to schedule which surgery types (see [31, 160, 192]). This can help to improve the robustness of planned OR schedules. Another example that integrates two higher decision levels (i.e., case mix planning and master surgery scheduling) is to add some flexibility when dividing and allocating the OR capacity to the surgical disciplines. Specifically, future research can build further on the research of several authors on flexible block scheduling [62, 177], in which either some OR blocks are allocated and others are left flexible, or the unused OR blocks are released some days (e.g., one week) before surgery. These flexible/unused OR blocks can then be used by the disciplines that face the highest need for OR time in that week. If this is the case, it is important to identify key indicators that can objectively measure this need and can guide the allocation of the flexible ORs. These topics are receiving attention in recent years since they can capture many benefits without much effort in theory and in practice.

6.3. *Inpatient surgery scheduling in practice*

From this literature review, it seems that the surgery activities in an outpatient setting could be planned and scheduled more effectively, whereas it would be challenging to plan OR capacity in a more uncertain and complex inpatient setting. Despite the different features, some of the beneficial practices in the outpatient context may be borrowed and used in the inpatient setting. In this respect, we propose that a promising practice is to perform a separate treatment of the more predictable inpatient surgeries that mainly consist of more routine surgeries with less variable surgery durations. One practical motivation for this idea is inspired by our university hospital which indicates that the scheduling of its inpatient operating theater might be improved by treating some of the inpatient surgeries in the way its outpatients are treated.

Specifically, we recommend that the whole surgery population is partitioned into two homogeneous groups, namely the more predictable surgeries (MPS) and the less predictable surgeries (LPS), and each of the two surgery groups is scheduled in different ORs. In order to partition surgeries into the MPS group and the LPS group, surgery duration characteristics (i.e., expected duration and duration variability) can be considered as a useful basis. This is due to the fact that the estimated surgery durations are always used in the process of surgery scheduling, on the one hand. On the other hand, our literature review indicates that the shorter surgery duration and lower variability facilitate a better performance of surgery scheduling. For instance, if we let the MPS inpatient group include surgeries that have a shorter surgery duration and a lower CV in the duration, this would typically lead the MPS group to include less complex and less variable surgeries, and the opposite for the LPS group.

This practice we propose relates to the work studying whether routine outpatient surgeries and complex inpatient surgeries should be pooled or separated in ORs [38, 169, 173, 191]. The reason is that we partition the more predictable inpatient surgeries, which in some way have resemblance to the outpatient surgeries, from the less predictable inpatient surgeries. In reality, increasing outpatient surgery rates are enabling more surgeries to be performed in the outpatient facilities, which to a large degree reveals the successful application of the separation of outpatient surgeries and inpatient surgeries on hospital resources. In this case, it seems that a higher scheduling efficiency for the more predictable inpatient surgeries can be guaranteed, and we might be able to improve the overall performance of inpatient surgery scheduling. In addition, more attention can be paid to the scheduling of the less predictable inpatient surgeries by using more flexible/robust strategies in order to cope with the greater difficulty in predicting those surgery activities.

Given that inpatient surgeries could be divided into MPS and LPS groups, there would be different policies to manage the access of both patient groups to the ORs at lower decision levels. We assume a dynamic surgery scheduling environment where each patient is scheduled to a surgery date and OR at consultation time. Then, these scheduling policies are defined as pooling policy, complete partitioning policy and partial partitioning policy, which are illustrated in Figure 6. With the first policy, a pool of ORs are shared between the MPS and LPS patient groups (e.g., within a surgical discipline). In this sense, there is no distinction between both groups when scheduling surgeries, which is now common practice in reality. With the complete partitioning policy, the MPS patients and the LPS patients can only be scheduled in their own ORs. In contrast, the partial partitioning policy adds an overflow mechanism to the complete partitioning policy, i.e., a patient group (e.g., MPS) can access the other group of ORs (e.g., LPS) if needed. In this regard, different overflow directions are involved: MPS-to-LPS (A), LPS-to-MPS (B), and two-way overflow (C).

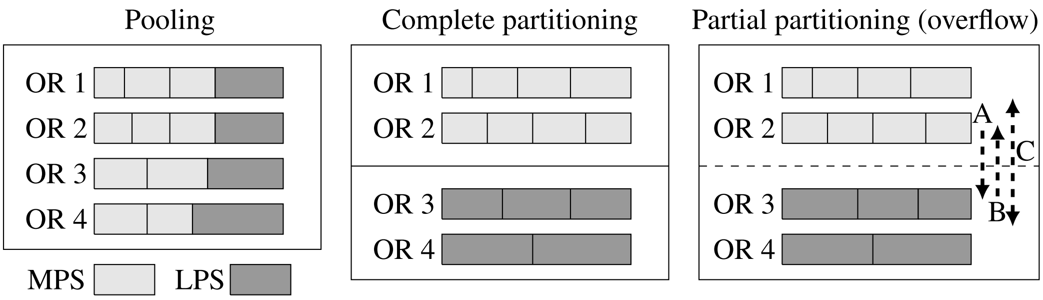


Figure 6: An illustration of patient access to ORs policies

Therefore, it is interesting to investigate these policies in different hospital inpatient surgical departments by considering their patient characteristics and capacity characteristics. If there exist non-elective surgeries that share OR capacity with the elective inpatient surgeries in the hospital, the non-elective surgeries are planned to use the LPS ORs due to their highly unpredictable nature.

7. Conclusion

In this paper, we provide the first thorough review of the papers published between 2000 and 2020 about the similarities and differences between outpatient surgery scheduling and inpatient surgery scheduling in hospitals. The literature is analyzed from three perspectives, i.e., the uncertainty incorporation, the research methodology, and a performance comparison between the two scheduling settings. Even though the inpatients and the outpatients experience the surgical services in a similar fashion in the hospital, the characteristics of many specific activities for them are substantially different. Table 9 summarizes the comparison between both scheduling settings. Specifically,

- The scheduling of inpatients suffers more from emergency patients, along with longer and more variable surgery durations, although there is a higher likelihood of no-shows for outpatients.
- As a result, outpatient surgery can provide better results in many of the performance measures (i.e., OR utilization, overtime, and patient cancellation rate) as opposed to inpatient surgery.
- On an inpatient basis, the LOS in the ward bed/ICU is often considered in the integrated OR planning and scheduling problem. In contrast, the PACU is a major bottleneck for the outpatient surgeries.
- There is no apparent trend on which methodologies are more popular in which setting (inpatient and outpatient). In terms of the decision levels, the offline operational level is most studied in both settings in the reviewed literature.

We also identify avenues for further research that provide opportunities for expanding existing methodologies and for narrowing the gap between theory and practice. A brief summary of them is shown in the following:

Table 9: Summary of comparisons between outpatient and inpatient surgery scheduling

Dimension	Specifics	Outpatient	Inpatient
Activities	No-show/unpunctuality	More	Less
	Emergency	Less	More
	Surgery duration mean	Shorter	Longer
	Surgery duration CV	Smaller	Larger
	Length of stay	< 1 day	≥ 1 day
Methodologies	Simulation	Discrete-event simulation, Monte Carlo simulation	
	Mathematical programming	Deterministic/stochastic models, robust optimization	
	Heuristics	Constructive heuristics, improvement heuristics	
	Analytical procedure	Markov Decision Process, queueing theory	
	Big data analytics	Machine learning, data mining	
PMs	OR utilization	Higher	Lower
	OR overtime	Lower	Higher
	Cancellation	Lower	Higher
	Patient waiting time	Direct	Indirect

Notes. There is no apparent trend on which methodologies are more popular in which scheduling setting. Direct waiting time (on the day of surgery) is often considered on an outpatient basis, while indirect waiting time (to be scheduled) is often considered on an inpatient basis.

- *Outpatient surgery scheduling.* There is a need for a more realistic representation of uncertain patterns in outpatient surgery scheduling. In addition, the indirect patient waiting time in the scheduling of outpatient surgery needs more attention.
- *Methodologies and decision levels.* Researchers need to be cautious in what research methodologies to apply because these methodologies are more or less related to the decision level and the complexity of the scheduling problem. Furthermore, the integration of multiple decision levels can be an interesting field.
- *Inpatient surgery scheduling in practice.* A promising practice for efficiently scheduling the inpatient surgical department is proposed which is to perform a separate treatment of the more predictable inpatients. In addition, we suggest how to partition the more predictable inpatient surgeries from the less predictable inpatient surgeries and how to schedule patients in the partitioning policies.

Declaration of interest

None.

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Appendix A.

Table A.1: List of important abbreviations

Abbreviation	Explanation
ASCs	Ambulatory surgery centers
BDA	Big data analytics
CV	Coefficient of variation
DES	Discrete-event simulation
DT	Due time
EL/NE	Elective/Non-elective
ICU	Intensive care unit
IN/OUT	Inpatient/Outpatient
LOS	Length of stay
LPS	Less predictable surgeries
MIP	Mixed integer programming
MPS	More predictable surgeries
MSSs	Master surgery schedules
ORs	Operating rooms
OT	Operating theater
PACU	Post-anesthesia care unit
PMs	Performance measures

References

[1] Abdelrasol, Z., Harraz, N., and Eltawil, A. (2014). Operating room scheduling problems: A survey and a proposed solution framework. In *Transactions on Engineering Technologies*, pages 717–731. Springer Netherlands, Dordrecht.

[2] Adan, I., Bekkers, J., Dellaert, N., Jeunet, J., and Vissers, J. (2011). Improving operational effectiveness of tactical master plans for emergency and elective patients under stochastic demand and capacitated resources. *European Journal of Operational Research*, 213(1):290–308.

[3] Adan, I., Bekkers, J., Dellaert, N., Vissers, J., and Yu, X. (2009). Patient mix optimisation and stochastic resource requirements: A case study in cardiothoracic surgery planning. *Health Care Management Science*, 12(2):129–141.

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

[5] Agnetis, A., Coppi, A., Corsini, M., Dellino, G., Meloni, C., and Pranzo, M. (2014). A decomposition approach for the combined master surgical schedule and surgical case assignment problems. *Health Care Management Science*, 17(1):49–59.

[6] Aissaoui, N. O., Khlif, H. H., and Zeghal, F. M. (2020). Integrated proactive surgery scheduling in private healthcare facilities. *Computers & Industrial Engineering*, 148:106686.

[7] Akbarzadeh, B., Moslehi, G., Reisi-Nafchi, M., and Maenhout, B. (2019). The re-planning and scheduling of surgical cases in the operating room department after block release time with resource rescheduling. *European Journal of Operational Research*, 278(2):596–614.

[8] Al Hasan, H., Guéret, C., Lemoine, D., and Rivreau, D. (2019). Surgical case scheduling with sterilising activity constraints. *International Journal of Production Research*, 57(10):2984–3002.

[9] Al-Refaie, A., Judeh, M., and Chen, T. (2018). Optimal multiple-period scheduling and sequencing of operating room and intensive care unit. *Operational Research*, 18(3):645–670.

[10] Allen, R. W., Taaffe, K. M., and Ritchie, G. (2014). Surgery rescheduling using discrete event simulation: A case study. In *Proceedings of the Winter Simulation Conference 2014*, pages 1365–1376. IEEE.

[11] Almaneea, L. I. and Hosny, M. I. (2018). A two level hybrid bees algorithm for operating room scheduling problem. In *Proceedings of the 2018 Science and Information Conference*, pages 272–290. Springer.

[12] Anjomshoa, H., Dumitrescu, I., Lustig, I., and Smith, O. J. (2018). An exact approach for tactical planning and patient selection for elective surgeries. *European Journal of Operational Research*, 268(2):728–739.

[13] Antonelli, D. and Taurino, T. (2010). Application of a patient flow model to a surgery department. In *2010 IEEE Workshop on Health Care Management*, pages 1–6. IEEE.

[14] Aringhieri, R., Landa, P., Soriano, P., Tànfani, E., and Testi, A. (2015). A two level metaheuristic for the operating room scheduling and assignment problem. *Computers & Operations Research*, 54:21–34.

[15] Azari-Rad, S., Yontef, A., Aleman, D. M., and Urbach, D. R. (2014). A simulation model for perioperative process improvement. *Operations Research for Health Care*, 3(1):22–30.

[16] Azari-Rad, S., Yontef, A. L., Aleman, D. M., and Urbach, D. R. (2013). Reducing elective general surgery cancellations at a canadian hospital. *Canadian Journal of Surgery*, 56(2):113–118.

[17] BADS (2021). The British Association Of Day Surgery (BADS) directory of procedures. https://bads.co.uk/publications/ Accessed May 2021.

[18] Ballard, S. M. and Kuhl, M. E. (2006). The use of simulation to determine maximum capacity in the surgical suite operating room. In *Proceedings of the 2006 Winter Simulation Conference*, pages 433–438. IEEE.

[19] Ballestín, F., Pérez, Á., and Quintanilla, S. (2019). Scheduling and rescheduling elective patients in operating rooms to minimise the percentage of tardy patients. *Journal of Scheduling*, 22(1):107–118.

[20] Bam, M., Denton, B. T., Van Oyen, M. P., and Cowen, M. E. (2017). Surgery scheduling with recovery resources. *IISE Transactions*, 49(10):942–955.

[21] Bam, M., Zhang, Z., Denton, B. T., Duck, M., and Van Oyen, M. P. (2020). Planning models for skills-sensitive surgical nurse staffing: A case study at a large academic medical center. *IISE Transactions on Healthcare Systems Engineering*, 10(4):277–293.

[22] Bandi, C. and Gupta, D. (2020). Operating room staffing and scheduling. *Manufacturing & Service Operations Management*.

[23] Banditori, C., Cappanera, P., and Visintin, F. (2013). A combined optimization-simulation approach to the master surgical scheduling problem. *IMA Journal of Management Mathematics*, 24(2):155–187.

[24] Banditori, C., Cappanera, P., and Visintin, F. (2014). Investigating the relationship between resources balancing and robustness in master surgical scheduling. In *Proceedings of the 2014 International Conference on Health Care Systems Engineering*, pages 149–162. Springer.

[25] Barz, C. and Rajaram, K. (2015). Elective patient admission and scheduling under multiple resource constraints. *Production and Operations Management*, 24(12):1907–1930.

[26] Bavafa, H., Leys, C. M., Örmeci, L., and Savin, S. (2019). Managing portfolio of elective surgical procedures: A multidimensional inverse newsvendor problem. *Operations Research*, 67(6):1543–1563.

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

[28] Beliën, J. and Demeulemeester, E. (2008). A branch-and-price approach for integrating nurse and surgery scheduling. *European journal of operational research*, 189(3):652–668.

[29] Beliën, J., Demeulemeester, E., and Cardoen, B. (2006). Visualizing the demand for various resources as a function of the master surgery schedule: A case study. *Journal of Medical Systems*, 30(5):343–350.

[30] Beliën, J., Demeulemeester, E., and Cardoen, B. (2009). A decision support system for cyclic master surgery scheduling with multiple objectives. *Journal of Scheduling*, 12(2):147–161.

[31] Benchoff, B., Yano, C. A., and Newman, A. (2017). Kaiser permanente oakland medical center optimizes operating room block schedule for new hospital. *Interfaces*, 47(3):214–229.

[32] Berg, B., Denton, B., Nelson, H., Balasubramanian, H., Rahman, A., Bailey, A., and Lindor, K. (2010). A discrete event simulation model to evaluate operational performance of a colonoscopy suite. *Medical Decision Making*, 30(3):380–387.

[33] Berg, B. P. and Denton, B. T. (2017). Fast approximation methods for online scheduling of outpatient procedure centers. *INFORMS Journal on Computing*, 29(4):631–644.

[34] Berg, B. P., Denton, B. T., Erdogan, S. A., Rohleder, T., and Huschka, T. (2014). Optimal booking and scheduling in outpatient procedure centers. *Computers & Operations Research*, 50:24–37.

[35] Blake, J. T. and Carter, M. W. (2002). A goal programming approach to strategic resource allocation in acute care hospitals. *European Journal of Operational Research*, 140(3):541–561.

[36] Bovim, T. R., Christiansen, M., Gullhav, A. N., Range, T. M., and Hellemo, L. (2020). Stochastic master surgery scheduling. *European Journal of Operational Research*.

[37] Bowers, J. (2013). Balancing operating theatre and bed capacity in a cardiothoracic centre. *Health Care Management Science*, 16(3):236–244.

[38] Bowers, J. and Mould, G. (2005). Ambulatory care and orthopaedic capacity planning. *Health Care Management Science*, 8(1):41–47.

[39] Burns, P., Konda, S., and Alvarado, M. (2020). Discrete-event simulation and scheduling for mohs micrographic surgery. *Journal of Simulation*, pages 1–15.

[40] Calegari, R., Fogliatto, F. S., Lucini, F. R., Anzanello, M. J., and Schaan, B. D. (2020). Surgery scheduling heuristic considering or downstream and upstream facilities and resources. *BMC Health Services Research*, 20:1–11.

[41] Cappanera, P., Visintin, F., and Banditori, C. (2014). Comparing resource balancing criteria in master surgical scheduling: A combined optimisation-simulation approach. *International Journal of Production Economics*, 158:179–196.

[42] Cappanera, P., Visintin, F., and Banditori, C. (2018). Addressing conflicting stakeholders' priorities in surgical scheduling by goal programming. *Flexible Services and Manufacturing Journal*, 30(1):252–271.

[43] Cardoen, B. and Demeulemeester, E. (2008). Capacity of clinical pathways: A strategic multi-level evaluation tool. *Journal of Medical Systems*, 32(6):443–452.

[44] Cardoen, B., Demeulemeester, E., and Beliën, J. (2009a). Optimizing a multiple objective surgical case sequencing problem. *International Journal of Production Economics*, 119(2):354–366.

[45] Cardoen, B., Demeulemeester, E., and Beliën, J. (2009b). Sequencing surgical cases in a day-care environment: An exact branch-and-price approach. *Computers & Operations Research*, 36(9):2660–2669.

[46] Cardoen, B., Demeulemeester, E., and Beliën, J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research*, 201(3):921–932.

[47] Castro, P. M. and Marques, I. (2015). Operating room scheduling with generalized disjunctive programming. *Computers & Operations Research*, 64:262–273.

[48] Ceschia, S. and Schaerf, A. (2016). Dynamic patient admission scheduling with operating room constraints, flexible horizons, and patient delays. *Journal of Scheduling*, 19(4):377–389.

[49] Chabouh, S., Hammami, S., Marcon, E., and Bouchriha, H. (2018). Appointment scheduling of inpatients and outpatients in a multistage integrated surgical suite: Application to a tunisian ophthalmology surgery department. *Journal of Simulation*, 12(1):67–75.

[50] Chow, V. S., Puterman, M. L., Salehirad, N., Huang, W., and Atkins, D. (2011). Reducing surgical ward congestion through improved surgical scheduling and uncapacitated simulation. *Production and Operations Management*, 20(3):418–430.

[51] Conforti, D., Guerriero, F., and Guido, R. (2010). A multi-objective block scheduling model for the management of surgical

operating rooms: New solution approaches via genetic algorithms. In *2010 IEEE Workshop on Health Care Management*, pages 1–5. IEEE.

[52] Dellaert, N., Cayiroglu, E., and Jeunet, J. (2016). Assessing and controlling the impact of hospital capacity planning on the waiting time. *International Journal of Production Research*, 54(8):2203–2214.

[53] Dellaert, N. and Jeunet, J. (2008). Hospital admission planning to optimize major resources utilization under uncertainty. In *Proceedings of the 2008 World Conference on Production and Operations Management*, page 16. Wiley Online Library.

[54] Deng, Y., Shen, S., and Denton, B. (2019). Chance-constrained surgery planning under conditions of limited and ambiguous data. *INFORMS Journal on Computing*, 31(3):559–575.

[55] Denton, B., Viapiano, J., and Vogl, A. (2007). Optimization of surgery sequencing and scheduling decisions under uncertainty. *Health Care Management Science*, 10(1):13–24.

[56] Denton, B. T., Rahman, A. S., Nelson, H., and Bailey, A. C. (2006). Simulation of a multiple operating room surgical suite. In *Proceedings of the 2006 Winter Simulation Conference*, pages 414–424. IEEE.

[57] Dexter, F. (2021). Bibliography of operating room management articles. https://www.franklindexter.net/ Accessed August 2021.

[58] Dexter, F., Blake, J. T., Penning, D. H., Sloan, B., Chung, P., and Lubarsky, D. A. (2002a). Use of linear programming to estimate impact of changes in a hospital's operating room time allocation on perioperative variable costs. *Anesthesiology*, 96(3):718–724.

[59] Dexter, F., Epstein, R. H., and Rodriguez, L. I. (2019). Throughout the United States, pediatric patients undergoing ambulatory surgery enter the operating room and are discharged earlier in the day than are adults. *Perioperative Care and Operating Room Management*, 16:100076.

[60] Dexter, F., Epstein, R. H., Traub, R. D., and Xiao, Y. (2004). Making management decisions on the day of surgery based on operating room efficiency and patient waiting times. *Anesthesiology*, 101(6):1444–1453.

[61] Dexter, F., Lubarsky, D. A., and Blake, J. T. (2002b). Sampling error can significantly affect measured hospital financial performance of surgeons and resulting operating room time allocations. *Anesthesia & Analgesia*, 95(1):184–188.

[62] Dexter, F. and Macario, A. (2004). When to release allocated operating room time to increase operating room efficiency. *Anesthesia & Analgesia*, 98(3):758–762.

[63] Dexter, F., Macario, A., and Lubarsky, D. A. (2001). The impact on revenue of increasing patient volume at surgical suites with relatively high operating room utilization. *Anesthesia & Analgesia*, 92(5):1215–1221.

[64] Dexter, F., Maxbauer, T., Stout, C., Archbold, L., and Epstein, R. H. (2014). Relative influence on total cancelled operating room time from patients who are inpatients or outpatients preoperatively. *Anesthesia & Analgesia*, 118(5):1072–1080.

[65] Dexter, F., Wachtel, R. E., Epstein, R. H., Ledolter, J., and Todd, M. M. (2010). Analysis of operating room allocations to optimize scheduling of specialty rotations for anesthesia trainees. *Anesthesia & Analgesia*, 111(2):520–524.

[66] Epstein, R. H. and Dexter, F. (2015). Management implications for the perioperative surgical home related to inpatient case cancellations and add-on case scheduling on the day of surgery. *Anesthesia & Analgesia*, 121(1):206–218.

[67] Erdogan, S. A. and Denton, B. T. (2011). Surgery planning and scheduling. In *Wiley Encyclopedia of Operations Research and Management Science*. Wiley Hoboken.

[68] Ewen, H. and Mönch, L. (2014). A simulation-based framework to schedule surgeries in an eye hospital. *IIE Transactions on Healthcare Systems Engineering*, 4(4):191–208.

[69] Fairley, M., Scheinker, D., and Brandeau, M. L. (2019). Improving the efficiency of the operating room environment with an optimization and machine learning model. *Health Care Management Science*, 22(4):756–767.

[70] Fei, H., Meskens, N., and El-Darzi, E. (2010). Evaluating alternative surgery plans with discrete-event simulation model. In *2010 IEEE Workshop on Health Care Management*, pages 1–6. IEEE.

[71] Ferrand, Y. B., Magazine, M. J., and Rao, U. S. (2014). Managing operating room efficiency and responsiveness for emergency and elective surgeries—a literature survey. *IIE Transactions on Healthcare Systems Engineering*, 4(1):49–64.

[72] Ferrin, D. M., Miller, M. J., Wininger, S., and Neuendorf, M. S. (2004). Analyzing incentives and scheduling in a major metropolitan hospital operating room through simulation. In *Proceedings of the 2004 Winter Simulation Conference*, pages

1975–1980. IEEE.

[73] Frack, B., Grabenstatter, K., and Williamson, J. (2017). Ambulatory surgery centers: Becoming big business. *LEK Consulting*, 19(25).

[74] Freeman, N., Zhao, M., and Melouk, S. (2018). An iterative approach for case mix planning under uncertainty. *Omega*, 76:160–173.

[75] Fügener, A. (2015). An integrated strategic and tactical master surgery scheduling approach with stochastic resource demand. *Journal of Business Logistics*, 36(4):374–387.

[76] Fügener, A., Edenharter, G. M., Kiefer, P., Mayr, U., Schiele, J., Steiner, F., Kolisch, R., and Blobner, M. (2016). Improving intensive care unit and ward utilization by adapting master surgery schedules. *A & A Case Reports*, 6(6):172–180.

[77] Fügener, A., Hans, E. W., Kolisch, R., Kortbeek, N., and Vanberkel, P. T. (2014). Master surgery scheduling with consideration of multiple downstream units. *European Journal of Operational Research*, 239(1):227–236.

[78] Ghazalbash, S., Sepehri, M. M., Shadpour, P., and Atighehchian, A. (2012). Operating room scheduling in teaching hospitals. *Advances in Operations Research*, 2012:e548493.

[79] Gomes, C., Almada-Lobo, B., Borges, J., and Soares, C. (2012). Integrating data mining and optimization techniques on surgery scheduling. In *Proceedings of the 2012 International Conference on Advanced Data Mining and Applications*, pages 589–602. Springer.

[80] Gonzalez, P. and Herrero, C. (2004). Optimal sharing of surgical costs in the presence of queues. *Mathematical Methods of Operations Research*, 59(3):435–446.

[81] Guda, H., Dawande, M., Janakiraman, G., and Jung, K. S. (2016). Optimal policy for a stochastic scheduling problem with applications to surgical scheduling. *Production and Operations Management*, 25(7):1194–1202.

[82] Guerriero, F. and Guido, R. (2011). Operational research in the management of the operating theatre: A survey. *Health Care Management Science*, 14(1):89–114.

[83] Gul, S., Denton, B. T., and Fowler, J. W. (2015). A progressive hedging approach for surgery planning under uncertainty. *INFORMS Journal on Computing*, 27(4):755–772.

[84] Gul, S., Denton, B. T., Fowler, J. W., and Huschka, T. (2011). Bi-criteria scheduling of surgical services for an outpatient procedure center. *Production and Operations Management*, 20(3):406–417.

[85] Gupta, D. (2007). Surgical suites' operations management. *Production and Operations Management*, 16(6):689–700.

[86] Gupta, D., Natarajan, M. K., Gafni, A., Wang, L., Shilton, D., Holder, D., and Yusuf, S. (2007). Capacity planning for cardiac catheterization: A case study. *Health Policy*, 82(1):1–11.

[87] Hachicha, H. K. and Mansour, F. Z. (2018). Two-milp models for scheduling elective surgeries within a private healthcare facility. *Health Care Management Science*, 21(3):376–392.

[88] Hamid, M., Hamid, M., Musavi, M., and Azadeh, A. (2019a). Scheduling elective patients based on sequence-dependent setup times in an open-heart surgical department using an optimization and simulation approach. *Simulation*, 95(12):1141–1164.

[89] Hamid, M., Nasiri, M. M., Werner, F., Sheikhahmadi, F., and Zhalechian, M. (2019b). Operating room scheduling by considering the decision-making styles of surgical team members: A comprehensive approach. *Computers & Operations Research*, 108:166–181.

[90] Hans, E., Wullink, G., van Houdenhoven, M., and Kazemier, G. (2008). Robust surgery loading. *European Journal of Operational Research*, 185(3):1038–1050.

[91] Hans, E. W. and Vanberkel, P. T. (2012). Operating theatre planning and scheduling. In *Handbook of Healthcare System Scheduling*, pages 105–130. Springer.

[92] Heider, S., Schoenfelder, J., McRae, S., Koperna, T., and Brunner, J. O. (2020). Tactical scheduling of surgeries to level bed utilization in the intensive care unit. *IISE Transactions on Healthcare Systems Engineering*, pages 1–14.

[93] Hof, S., Fügener, A., Schoenfelder, J., and Brunner, J. O. (2017). Case mix planning in hospitals: A review and future agenda. *Health Care Management Science*, 20(2):207–220.

[94] Hsu, V. N., de Matta, R., and Lee, C. Y. (2003). Scheduling patients in an ambulatory surgical center. *Naval Research Logistics*, 50(3):218–238.

[95] Hulshof, P. J., Boucherie, R. J., Van Essen, J. T., Hans, E. W., Hurink, J. L., Kortbeek, N., Litvak, N., Vanberkel, P. T., Van Der Veen, E., Veltman, B., et al. (2011). Orchestra: An online reference database of OR/MS literature in health care. *Health Care Management Science*, 14(4):383–384.

[96] Huschka, T. R., Denton, B. T., Gul, S., and Fowler, J. W. (2007). Bi-criteria evaluation of an outpatient procedure center via simulation. In *Proceedings of the 2007 Winter Simulation Conference*, pages 1510–1518. IEEE.

[97] Jarrett, P. and Staniszewski, A. (2006). The development of ambulatory surgery and future challenges. *London: The International Association for Ambulatory Surgery*.

[98] Jeang, A. and Chiang, A.-J. (2012). Economic and quality scheduling for effective utilization of operating rooms. *Journal of Medical Systems*, 36(3):1205–1222.

[99] Jebali, A., Alouane, A. B. H., and Ladet, P. (2006). Operating rooms scheduling. *International Journal of Production Economics*, 99(1-2):52–62.

[100] Jebali, A. and Diabat, A. (2015). A stochastic model for operating room planning under capacity constraints. *International Journal of Production Research*, 53(24):7252–7270.

[101] Jebali, A. and Diabat, A. (2017). A chance-constrained operating room planning with elective and emergency cases under downstream capacity constraints. *Computers & Industrial Engineering*, 114:329–344.

[102] Jittamai, P. and Kangwansura, T. (2011). A hospital admission planning model for emergency and elective patients under stochastic resource requirements and no-shows. In *Proceedings of the 2011 IEEE International Conference on Industrial Engineering and Engineering Management*, pages 166–170. IEEE.

[103] Joustra, P. E., de Wit, J., Van Dijk, N. M., and Bakker, P. J. M. (2011). How to juggle priorities? an interactive tool to provide quantitative support for strategic patient-mix decisions: An ophthalmology case. *Health Care Management Science*, 14(4):348–360.

[104] Kadhim, M., Gans, I., Baldwin, K., Flynn, J., and Ganley, T. (2016). Do surgical times and efficiency differ between inpatient and ambulatory surgery centers that are both hospital owned? *Journal of Pediatric Orthopaedics*, 36(4):423–428.

[105] Kamran, M. A., Karimi, B., and Dellaert, N. (2018). Uncertainty in advance scheduling problem in operating room planning. *Computers & Industrial Engineering*, 126:252–268.

[106] Kamran, M. A., Karimi, B., and Dellaert, N. (2020). A column-generation-heuristic-based benders' decomposition for solving adaptive allocation scheduling of patients in operating rooms. *Computers & Industrial Engineering*, 148:106698.

[107] Kheiri, A., Lewis, R., Thompson, J., and Harper, P. (2020). Constructing operating theatre schedules using partitioned graph colouring techniques. *Health Systems*, pages 1–12.

[108] Kong, Q., Li, S., Liu, N., Teo, C.-P., and Yan, Z. (2020). Appointment scheduling under time-dependent patient no-show behavior. *Management Science*, 66(8):3480–3500.

[109] Kroer, L. R., Foverskov, K., Vilhelmsen, C., Hansen, A. S., and Larsen, J. (2018). Planning and scheduling operating rooms for elective and emergency surgeries with uncertain duration. *Operations Research for Health Care*, 19:107–119.

[110] Kumar, A., Costa, A. M., Fackrell, M., and Taylor, P. G. (2018). A sequential stochastic mixed integer programming model for tactical master surgery scheduling. *European Journal of Operational Research*, 270(2):734–746.

[111] Kuo, P. C., Schroeder, R. A., Mahaffey, S., and Bollinger, R. R. (2003). Optimization of operating room allocation using linear programming techniques. *Journal of the American College of Surgeons*, 197(6):889–895.

[112] Landa, P., Aringhieri, R., Soriano, P., Tànfani, E., and Testi, A. (2016). A hybrid optimization algorithm for surgeries scheduling. *Operations Research for Health Care*, 8:103–114.

[113] Latorre-Núñez, G., Lüer-Villagra, A., Marianov, V., Obreque, C., Ramis, F., and Neriz, L. (2016). Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. *Computers & Industrial Engineering*, 97:248–257.

[114] Lehtonen, J.-M., Torkki, P., Peltokorpi, A., and Moilanen, T. (2013). Increasing operating room productivity by duration categories and a newsvendor model. *International Journal of Health Care Quality Assurance*, 26(2):80–92.

[115] Lewis, H. F., Sexton, T. R., and Dolan, M. A. (2011). An efficiency-based multicriteria strategic planning model for ambulatory surgery centers. *Journal of Medical Systems*, 35(5):1029–1037.

[116] Li, X., Rafaliya, N., Baki, M. F., and Chaouch, B. A. (2017). Scheduling elective surgeries: The tradeoff among bed capacity, waiting patients and operating room utilization using goal programming. *Health Care Management Science*, 20(1):33–54.

[117] Lin, R.-C., Sir, M. Y., and Pasupathy, K. S. (2013). Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: Specific application to determining optimal resource levels in surgical services. *Omega*, 41(5):881–892.

[118] Liu, N., Truong, V.-A., Wang, X., and Anderson, B. R. (2019). Integrated scheduling and capacity planning with considerations for patients' length-of-stays. *Production and Operations Management*, 28(7):1735–1756.

[119] Luo, L., Liu, C., Feng, L., Zhao, S., and Gong, R. (2018). A random forest and simulation approach for scheduling operation rooms: elective surgery cancelation in a chinese hospital urology department. *The International Journal of Health Planning and Management*, 33(4):941–966.

[120] Luo, L., Luo, Y., and Qin, C. (2017). Admission control policies for surgery patients. *Journal of Medical Systems*, 41(8):1–16.

[121] Ma, G. and Demeulemeester, E. (2013). A multilevel integrative approach to hospital case mix and capacity planning. *Computers & Operations Research*, 40(9):2198–2207.

[122] Marcon, E., Kharraja, S., Smolski, N., Luquet, B., and Viale, J. P. (2003). Determining the number of beds in the postanesthesia care unit: a computer simulation flow approach. *Anesthesia & Analgesia*, 96(5):1415–1423.

[123] Marques, I. and Captivo, M. E. (2015). Bicriteria elective surgery scheduling using an evolutionary algorithm. *Operations Research for Health Care*, 7:14–26.

[124] Marques, I. and Captivo, M. E. (2017). Different stakeholders' perspectives for a surgical case assignment problem: Deterministic and robust approaches. *European Journal of Operational Research*, 261(1):260–278.

[125] Marques, I., Captivo, M. E., and Barros, N. (2019). Optimizing the master surgery schedule in a private hospital. *Operations Research for Health Care*, 20:11–24.

[126] Marques, I., Captivo, M. E., and Pato, M. V. (2012). An integer programming approach to elective surgery scheduling. *OR Spectrum*, 34(2):407–427.

[127] Marques, I., Captivo, M. E., and Pato, M. V. (2014). Scheduling elective surgeries in a portuguese hospital using a genetic heuristic. *Operations Research for Health Care*, 3(2):59–72.

[128] Marques, I., Captivo, M. E., and Pato, M. V. (2015). A bicriteria heuristic for an elective surgery scheduling problem. *Health Care Management Science*, 18(3):251–266.

[129] May, J. H., Spangler, W. E., Strum, D. P., and Vargas, L. G. (2011). The surgical scheduling problem: Current research and future opportunities. *Production and Operations Management*, 20(3):392–405.

[130] McRae, S. and Brunner, J. O. (2020). Assessing the impact of uncertainty and the level of aggregation in case mix planning. *Omega*, 97:102086.

[131] M'Hallah, R. and Al-Roomi, A. H. (2014). The planning and scheduling of operating rooms: A simulation approach. *Computers & Industrial Engineering*, 78:235–248.

[132] M'Hallah, R. and Visintin, F. (2019). A stochastic model for scheduling elective surgeries in a cyclic master surgical schedule. *Computers & Industrial Engineering*, 129:156–168.

[133] Molina-Pariente, J. M., Hans, E. W., Framinan, J. M., and Gomez-Cia, T. (2015). New heuristics for planning operating rooms. *Computers & Industrial Engineering*, 90:429–443.

[134] Moosavi, A. and Ebrahimnejad, S. (2020). Robust operating room planning considering upstream and downstream units: A new two-stage heuristic algorithm. *Computers & Industrial Engineering*, 143:106387.

[135] Mulholland, M. W., Abrahamse, P., and Bahl, V. (2005). Linear programming to optimize performance in a department of surgery. *Journal of the American College of Surgeons*, 200(6):861–868.

[136] Nazif, H. (2018). Operating room surgery scheduling with fuzzy surgery durations using a metaheuristic approach. *Advances in Operations Research*, 2018:e8637598.

[137] NCEPOD (2021). The NCEPOD classification of intervention based on urgency. https://www.ncepod.org.uk/classification.html Accessed August 2021.

[138] Nemati, S., Shylo, O. V., Prokopyev, O. A., and Schaefer, A. J. (2016). The surgical patient routing problem: A central

planner approach. *INFORMS Journal on Computing*, 28(4):657–673.

[139] Neyshabouri, S. and Berg, B. P. (2017). Two-stage robust optimization approach to elective surgery and downstream capacity planning. *European Journal of Operational Research*, 260(1):21–40.

[140] Nguyen, T., Li, Z., Spiegler, V., Ieromonachou, P., and Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, 98:254–264.

[141] Ozen, A., Marmor, Y., Rohleder, T., Balasubramanian, H., Huddleston, J., and Huddleston, P. (2016). Optimization and simulation of orthopedic spine surgery cases at mayo clinic. *Manufacturing & Service Operations Management*, 18(1):157–175.

[142] Pariente, J. M. M., Torres, J. M. F., and Cia, T. G. (2009). Policies and decision models for solving elective case operating room scheduling. In *Proceedings of the 2009 International Conference on Computers & Industrial Engineering*, pages 112–117. IEEE.

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

[144] Pham, D. N. and Klinkert, A. (2008). Surgical case scheduling as a generalized job shop scheduling problem. *European Journal of Operational Research*, 185(3):1011–1025.

[145] Philip, B. K. (2012). Day care surgery: The United States model of health care. *Ambulatory Surgery*, 17(4):81–82.

[146] Quemby, D. J. and Stocker, M. E. (2014). Day surgery development and practice: key factors for a successful pathway. *Continuing Education in Anaesthesia, Critical Care & Pain*, 14(6):256–261.

[147] Rachuba, S. and Werners, B. (2014). A robust approach for scheduling in hospitals using multiple objectives. *Journal of the Operational Research Society*, 65(4):546–556.

[148] Rachuba, S. and Werners, B. (2017). A fuzzy multi-criteria approach for robust operating room schedules. *Annals of Operations Research*, 251(1-2):325–350.

[149] Ramis, F. J., Palma, J. L., and Baesler, F. F. (2001). The use of simulation for process improvement at an ambulatory surgery center. In *Proceedings of the 2001 Winter Simulation Conference*, pages 1401–1404. IEEE.

[150] Rath, S., Rajaram, K., and Mahajan, A. (2017). Integrated anesthesiologist and room scheduling for surgeries: Methodology and application. *Operations Research*, 65(6):1460–1478.

[151] Reese, K., Avansino, J., Brumm, M., Martin, L., and Day, T. E. (2020). Determining future capacity for an ambulatory surgical center with discrete event simulation. *International Journal of Healthcare Management*, pages 1–6.

[152] Roshanaei, V., Booth, K. E., Aleman, D. M., Urbach, D. R., and Beck, J. C. (2020). Branch-and-check methods for multi-level operating room planning and scheduling. *International Journal of Production Economics*, 220:107433.

[153] Samudra, M., Demeulemeester, E., and Cardoen, B. (2013). A closer view at the patient surgery planning and scheduling problem: A literature review. *Review of Business and Economic Literature*, no:2013(iss:2).

[154] Samudra, M., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., and Rademakers, F. E. (2017). Due time driven surgery scheduling. *Health Care Management Science*, 20(3):326–352.

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

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

[157] Saremi, A., Jula, P., ElMekkawy, T., and Wang, G. G. (2013). Appointment scheduling of outpatient surgical services in a multistage operating room department. *International Journal of Production Economics*, 141(2):646–658.

[158] Schiele, J., Koperna, T., and Brunner, J. O. (2021). Predicting intensive care unit bed occupancy for integrated operating room scheduling via neural networks. *Naval Research Logistics*, 68(1):65–88.

[159] Schmid, V. and Doerner, K. F. (2014). Examination and operating room scheduling including optimization of intrahospital routing. *Transportation Science*, 48(1):59–77.

[160] Schneider, A. T., van Essen, J. T., Carlier, M., and Hans, E. W. (2020). Scheduling surgery groups considering multiple downstream resources. *European Journal of Operational Research*, 282(2):741–752.

[161] Shi, P., Dexter, F., and Epstein, R. H. (2016). Comparing policies for case scheduling within 1 day of surgery by markov chain models. *Anesthesia & Analgesia*, 122(2):526–538.

[162] Siqueira, C. L., Arruda, E. F., Bahiense, L., Bahr, G. L., and Motta, G. R. (2018). Long-term integrated surgery room optimization and recovery ward planning, with a case study in the brazilian national institute of traumatology and orthopedics (into). *European Journal of Operational Research*, 264(3):870–883.

[163] Soh, K. W., Walker, C., and O'Sullivan, M. (2017). A literature review on validated simulations of the surgical services. *Journal of Medical Systems*, 41(4):61.

[164] Souki, M. and Rebai, A. (2009). Memetic differential evolution algorithm for operating room scheduling. In *Proceedings of the 2009 International Conference on Computers & Industrial Engineering*, pages 845–850. IEEE.

[165] Souki, M. and Rebai, A. (2010). Heuristics for the operating theatre planning and scheduling. *Journal of Decision Systems*, 19(2):225–252.

[166] Souki, M., Youssef, S. B., and Rebai, A. (2009). Memetic algorithm for operating room admissions. In *Proceedings of the 2009 International Conference on Computers & Industrial Engineering*, pages 519–524. IEEE.

[167] Spratt, B. and Kozan, E. (2016). Waiting list management through master surgical schedules: A case study. *Operations Research for Health Care*, 10:49–64.

[168] Spratt, B., Kozan, E., and Sinnott, M. (2019). Analysis of uncertainty in the surgical department: Durations, requests and cancellations. *Australian Health Review*, 43(6):706–711.

[169] Steins, K., Persson, F., and Holmer, M. (2010). Increasing utilization in a hospital operating department using simulation modeling. *Simulation*, 86(8-9):463–480.

[170] Stuart, K. and Kozan, E. (2012). Reactive scheduling model for the operating theatre. *Flexible Services and Manufacturing Journal*, 24(4):400–421.

[171] Tànfani, E. and Testi, A. (2010). A pre-assignment heuristic algorithm for the master surgical schedule problem (mssp). *Annals of Operations Research*, 178(1):105–119.

[172] Testi, A. and Tànfani, E. (2009). Tactical and operational decisions for operating room planning: Efficiency and welfare implications. *Health Care Management Science*, 12(4):363–373.

[173] Tyler, D. C., Pasquariello, C. A., and Chen, C.-H. (2003). Determining optimum operating room utilization. *Anesthesia & Analgesia*, 96(4):1114–1121.

[174] Union, O. E. (2018). *Health at a Glance: Europe 2018 State of Health in the EU Cycle*. OECD.

[175] Vali-Siar, M. M., Gholami, S., and Ramezanian, R. (2018). Multi-period and multi-resource operating room scheduling under uncertainty: A case study. *Computers & Industrial Engineering*, 126:549–568.

[176] van den Broek d'Obrenan, A., Ridder, A., Roubos, D., and Stougie, L. (2020). Minimizing bed occupancy variance by scheduling patients under uncertainty. *European Journal of Operational Research*, 286(1):336–349.

[177] van der Kooij, R., Mes, M. R., and Hans, E. W. (2014). Simulation framework to analyze operating room release mechanisms. In *Proceedings of the 2014 Winter Simulation Conference*, pages 1144–1155. IEEE.

[178] van Essen, J. T., Bosch, J. M., Hans, E. W., van Houdenhoven, M., and Hurink, J. L. (2014). Reducing the number of required beds by rearranging the or-schedule. *OR Spectrum*, 36(3):585–605.

[179] van Essen, J. T., Hans, E. W., Hurink, J. L., and Oversberg, A. (2012). Minimizing the waiting time for emergency surgery. *Operations Research for Health Care*, 1(2-3):34–44.

[180] Van Houdenhoven, M., van Oostrum, J. M., Hans, E. W., Wullink, G., and Kazemier, G. (2007). Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical case scheduling. *Anesthesia & Analgesia*, 105(3):707–714.

[181] Van Huele, C. and Vanhoucke, M. (2014). Analysis of the integration of the physician rostering problem and the surgery scheduling problem. *Journal of Medical Systems*, 38(6):43.

[182] Van Huele, C. and Vanhoucke, M. (2015a). Decomposition-based heuristics for the integrated physician rostering and surgery scheduling problem. *Health Systems*, 4(3):159–175.

[183] Van Huele, C. and Vanhoucke, M. (2015b). Operating theatre modelling: integrating social measures. *Journal of Simulation*,

9(2):121–128.

[184] Van Riet, C. and Demeulemeester, E. (2015). Trade-offs in operating room planning for electives and emergencies: A review. *Operations Research for Health Care*, 7:52–69.

[185] Vanberkel, P. T. and Blake, J. T. (2007). A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. *Health Care Management Science*, 10(4):373–385.

[186] Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., van Lent, W., and van Harten, W. H. (2011a). An exact approach for relating recovering surgical patient workload to the master surgical schedule. *Journal of the Operational Research Society*, 62(10):1851–1860.

[187] Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., van Lent, W. A. M., and van Harten, W. H. (2011b). Accounting for inpatient wards when developing master surgical schedules. *Anesthesia & Analgesia*, 112(6):1472–1479.

[188] Vancroonenburg, W., De Causmaecker, P., and Berghe, G. V. (2019). Chance-constrained admission scheduling of elective surgical patients in a dynamic, uncertain setting. *Operations Research for Health Care*, 22:100196.

[189] Vansteenkiste, N., Lamote, C., Vandersmissen, J., Luysmans, P., Monnens, P., De Voldere, G., Kips, J., and Rademakers, F. E. (2012). Reallocation of operating room capacity using the due-time model. *Medical Care*, 50(9):779–784.

[190] Villarreal, M. C. and Keskinocak, P. (2016). Staff planning for operating rooms with different surgical services lines. *Health Care Management Science*, 19(2):144–169.

[191] Visintin, F., Cappanera, P., and Banditori, C. (2016). Evaluating the impact of flexible practices on the master surgical scheduling process: An empirical analysis. *Flexible Services and Manufacturing Journal*, 28(1-2):182–205.

[192] Visintin, F., Cappanera, P., Banditori, C., and Danese, P. (2017). Development and implementation of an operating room scheduling tool: An action research study. *Production Planning & Control*, 28(9):758–775.

[193] Vissers, J. M. H., Adan, I. J. B. F., and Bekkers, J. A. (2005). Patient mix optimization in tactical cardiothoracic surgery planning: A case study. *IMA Journal of Management Mathematics*, 16(3):281–304.

[194] Wachtel, R. E. and Dexter, F. (2007). A simple method for deciding when patients should be ready on the day of surgery without procedure-specific data. *Anesthesia & Analgesia*, 105(1):127–140.

[195] Wang, T., Meskens, N., and Duvivier, D. (2012). A comparison of mixed-integer programming and constraint programming models for scheduling problem in operating theatres. In *Proceedings of the 2012 International Conference on Information Systems, Logistics and Supply Chain*, pages 1–11. Springer.

[196] Wang, Y., Tang, J., and Fung, R. Y. K. (2014). A column-generation-based heuristic algorithm for solving operating theater planning problem under stochastic demand and surgery cancellation risk. *International Journal of Production Economics*, 158:28–36.

[197] Xiang, W., Yin, J., and Lim, G. (2015). An ant colony optimization approach for solving an operating room surgery scheduling problem. *Computers & Industrial Engineering*, 85:335–345.

[198] Xue, W., Yan, Z., Barnett, R., Fleisher, L., and Liu, R. (2013). Dynamics of elective case cancellation for inpatient and outpatient in an academic center. *Journal of Anesthesia & Clinical Research*, 4(5):314.

[199] Yahia, Z., Harraz, N., and Eltawil, A. B. (2014). Building master surgery schedules with leveled bed occupancy and nurse workloads. In *2014 IEEE International Conference on Industrial Engineering and Engineering Management*, pages 89–93. IEEE.

[200] Yip, K., Leung, L., and Yeung, D. (2018). Levelling bed occupancy: reconfiguring surgery schedules via simulation. *International Journal of Health Care Quality Assurance*.

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

[202] Zhang, J., Dridi, M., and El Moudni, A. (2017). A stochastic shortest-path mdp model with dead ends for operating rooms planning. In *Proceedings of the 2017 International Conference on Automation and Computing*, pages 1–6. IEEE.

[203] Zhang, J., Dridi, M., and El Moudni, A. (2019). A two-level optimization model for elective surgery scheduling with downstream capacity constraints. *European Journal of Operational Research*, 276(2):602–613.

[204] Zhang, J., Dridi, M., and El Moudni, A. (2020a). Column-generation-based heuristic approaches to stochastic surgery

scheduling with downstream capacity constraints. *International Journal of Production Economics*, 229:107764.

[205] Zhang, Y., Shen, S., and Erdogan, S. A. (2018). Solving 0–1 semidefinite programs for distributionally robust allocation of surgery blocks. *Optimization Letters*, 12(7):1503–1521.

[206] Zhang, Z., Denton, B. T., and Xie, X. (2020b). Branch and price for chance-constrained bin packing. *INFORMS Journal on Computing*, 32(3):547–564.

[207] Zhang, Z. and Xie, X. (2015). Simulation-based optimization for surgery appointment scheduling of multiple operating rooms. *IIE Transactions*, 47(9):998–1012.

[208] Zhang, Z., Xie, X., and Geng, N. (2012). Promise surgery start times and implementation strategies. In *Proceedings of the 2012 IEEE International Conference on Automation Science and Engineering*, pages 143–149. IEEE.

[209] Zhang, Z., Xie, X., and Geng, N. (2014). Dynamic surgery assignment of multiple operating rooms with planned surgeon arrival times. *IEEE Transactions on Automation Science and Engineering*, 11(3):680–691.

[210] Zhao, Z. and Li, X. (2014). Scheduling elective surgeries with sequence-dependent setup times to multiple operating rooms using constraint programming. *Operations Research for Health Care*, 3(3):160–167.

[211] Zhu, S., Fan, W., Yang, S., Pei, J., and Pardalos, P. M. (2019). Operating room planning and surgical case scheduling: A review of literature. *Journal of Combinatorial Optimization*, 37(3):757–805.

[212] Zhu, T., Luo, L., Shen, W., Xu, X., and Kou, R. (2020). Admission scheduling of inpatients by considering two inter-related resources: Beds and operating rooms. *Optimization*, pages 1–39.