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Scheduling operating rooms: achievements, challenges and pitfalls

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Scheduling operating rooms: Achievements, challenges and pitfalls

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Abstract In hospitals, the operating room (OR) is a particularly expensive facility and thus efficient scheduling is imperative. This can be greatly supported by using advanced methods that are discussed in the academic literature. In order to help researchers and practitioners to select new relevant articles, we classify the recent OR planning and scheduling literature into tables using patient type, used performance measures, decisions made, OR supporting units, uncertainty, research methodology and testing phase. Additionally, we identify promising practices and trends and recognize common pitfalls when researching OR scheduling. Our findings indicate, among others, that it is often unclear whether an article mainly targets researchers and thus contributes advanced methods or targets practitioners and consequently provides managerial insights. Moreover, many performance measures (e.g., overtime) are not always used in the correct context. Furthermore, we see that important information that would allow readers to determine whether the reported research results are relevant to them is often missing. In order to avoid these pitfalls, we conclude that researchers need to state whether they target researchers or practitioners, motivate the choice of the used performance measures and mention both setting and method specific assumptions.

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1 Introduction

Health care has a heavy financial burden for governments within the European Union as well as in the rest of the world. Additionally, while growing economies and newly emerging technologies could lead us to believe that supporting our respective national health care systems might get less expensive over time, data show that this is not the case.

For example, within the USA, the National Health Expenditure as a share of the Gross Domestic Product (GDP) was 17.4% in 2013 [54]. On the European continent, even though large differences exist across member states, health care expenditure as a share of the GDP was 8.7% in 2012 [193]. Hospitals are responsible for more than one third of these expenditures [86].

Within the hospital, considerable attention is given to operating rooms (ORs) as they represent a significant segment of hospital costs [120]. Out of the many aspects of OR management, we focus our attention on planning and scheduling problems (the terms planning and scheduling are in this article used interchangeably).

Given the importance of OR scheduling, it is not surprising that many research groups from the operations research community provide solution approaches to the problems that affect it. Reviews on this literature are important as they help researchers to select relevant articles for their research setting and serve as a guide for practitioners (e.g, hospital manager) to quickly find papers that can contain useful managerial insights.

Additionally, reviews preferably cover the following two important aspects. First, they help to identify promising practices and shows recent trends (i.e., hot topics). Second, they identify common pitfalls or important aspects to consider when doing researching in this field. To our knowledge, there is no recent review on OR planning that considers these latter two aspects.

In order to cover these aspects, we define the following three research tasks. First, to classify the recent OR planning and scheduling literature (Sec. 3.1-3.7) using a simple, but comprehensive framework. For this task, we build up on the work carried out by Cardoen et al. [42] and Demeulemeester et al. [60]. Second, to look for evolutions over time, common approaches and relations between the different classification fields (Sec. 3.1-3.8). Third, to identify the common pitfalls (e.g., information that we found missing in some articles) and to develop guidelines that can help researchers to avoid them (Sec. 4.1-4.3).

The purpose of the remaining sections is to explain the research method (Sec. 2.1), to position this paper in the existent group of reviews (Sec. 2.2), to introduce the classification fields (introduction of Sec. 3), to discuss the limitations of this study (Sec. 4.4) and to describe our main conclusions (Sec. 5).

2 Search Method and Other Reviews

In Sect. 2.1, we introduce the procedure that we used to identify relevant articles. In Sect. 2.2, we discuss the structure and scope of reviews written on similar topics and position our review within the context of this existing literature.

2.1 Search Method

We searched the databases Pubmed and Web of Science for relevant articles, which are written in English and appeared in 2000 or afterwards. Search phrases included combinations of the following words: operating, surgery, case, room, theatre(er), scheduling, planning and sequencing. We searched in both titles and abstracts and in addition checked the complete reference list of any already found article. As we endeavored to conduct the search process in an unbiased way, we believe we have obtained a set of articles that objectively represents the literature on OR planning. At the end of the search procedure, we identified 216 technically oriented papers. Note that we chose to investigate trends only from 2004 onwards as in the preceding years not enough articles were published to get reliable results (Table 1).

Table 1 The graphs showing trends are based on papers in the third column, while the tables additionally include the papers in the second column

	2000-2003	2004-2014
Journal	24	137
Proceedings	3	42
Other	0	10
Total	27	189

We define an article as “technical” if it contains an algorithmic description of a method directly related to OR scheduling. Some articles are missing this algorithmic component and instead provide managerial insights. Those articles are excluded from the classification tables, as not all classification fields apply to them, but some of their insights are mentioned in the text. The quantitative descriptions provided in Sec. 3.1-3.8, which give insights into the changing trends set by the research community, are exclusively based on the technical contributions.

The majority of the included articles are recent publications (Fig. 1). This reflects the trend that the amount of published technical articles has been increasing significantly in the recent ten years.

We do not include topics related to business process reengineering, the impact of introducing new technologies, facility design or long-term OR expansion. Also, articles that deal with appointment scheduling are excluded from this review. This is the case as some of the basic assumptions that apply to appointment scheduling are not valid for surgery scheduling. For a review on appointment scheduling, we refer to [48].

2.2 Other Reviews

In the past 60 years, a large body of literature on OR planning and scheduling has been published. The literature has been structured and reviewed by several authors, using a variety of classification techniques and frameworks. We grouped these reviews based on their scope and structure (Table 2).

Based on the scope of the literature review, we distinguish between three levels. The first level purely focuses on the OR department (including the post-anesthesia care unit (PACU) and the intensive care unit (ICU)). The second level targets

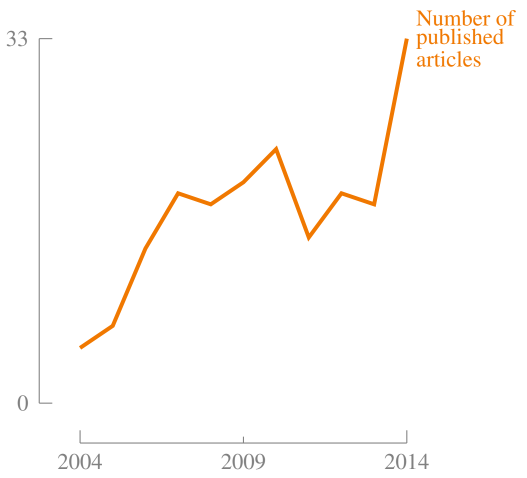

Fig. 1 The number of published technical articles in OR scheduling has been growing over the last decade

the OR together with other areas that can be of interest in a hospital such as bed planning [26] or patient flow planning. The third level covers OR management in the broader context of patient care and therefore often includes different care services [128].

In some of the literature reviews articles are classified based on the three hierarchical decision levels: strategic (long-term), tactical (medium-term) and operational (short-term). The strategic decision level involves decisions that affect both the number and the type of performed surgeries. The tactical level usually involves the construction of a cyclic schedule, which assigns time blocks to surgeons or surgeon groups. The final, operational level deals mostly with daily staffing and surgery scheduling decisions. Guerriero and Guido [105] also discuss papers that include a mix of the three levels. Similarly, Vissers et al. [262] propose a hierarchical framework for production control in healthcare. They distinguish between five levels and discuss for each level, amongst others, the type of decisions, the time horizon and the involved decision makers. With respect to the operational level, a further distinction can be made between off-line (i.e., before schedule execution) and on-line (i.e., during schedule execution) approaches [112].

In other literature reviews custom categories are used (Table 2). As such, Brailsford and Vissers [36] use the product life cycle stages to review 35 years of papers presented at the ORAHS conference. Moreover, Erdogan and Denton [82] review the literature according to the applied solution approach. Przasnyski [210] structures the literature based on general areas of concern, such as cost containment. Other reviews structure the literature on the basis of managerial or functional levels [207] and problem characteristics, e.g., the type of the arrival process [110].

Most literature reviews are not only reference points to articles, but also point out topics for future research. Guerriero and Guido [105] conclude that the three hierarchical levels are rarely studied together and argue that the tactical level has received increased attention in the last ten years. In contrast, Hans and Vanberkel [112] argue that future research should focus more on the tactical level.

Also, May et al. [179] make suggestions and argue that it might be promising to broaden the focus from operations research techniques to the economic and project management aspects of surgery scheduling. Additionally, Vissers et al. [262] suggest to put a larger emphasis on the multidisciplinary aspects of patient flow control systems and suggest to experiment with the effect of grouping patients in new ways, such as based on their length of stay (LOS) or surgery duration.

Furthermore, several authors emphasize that more research could be done on on-line rescheduling performed close to or on the day of surgery. Dexter et al. [73] provide a review on the few papers that include that type of decisions and emphasize the importance of the following four points: patient safety, open access to OR time, maximizing OR efficiency (defined as minimal overutilized OR time) and minimizing patient waiting time. Other reviews emphasize the need for more detailed models on the seasonality of demand, for more realistic constraints for surgeon and patient preferences and for a larger focus on the entire care pathway.

We generally observe in reviews that topics such as staffing are often excluded and thus treated separately from the resource related decision making problems. Finally, we also observe that, unlike in the diagnostic imaging scheduling literature, most focus is on models where patients are scheduled in batches and not one-by-one.

Table 2 Existing reviews differ in their scope (*rows*) and classification structure (*columns*)

	Hierarchical categories	Custom categories
OR	[105, 112]	[42, 60, 73, 82, 109, 167, 179, 210, 219]
Hospital	[26, 27, 32, 262]	[27, 32, 137, 231, 232, 250, 255]
Health care	[112, 127, 128]	[36, 110, 112, 127, 128, 207]

Reviewing the literature according to hierarchal categories is a common approach. Articles appearing twice in the table use a multi-dimensional classification structure

In this review, we propose a structure that is based on descriptive fields. We are not using hierarchical levels, since the boundaries between these levels can vary considerably for different settings and hence are often perceived as vague and interrelated [230]. Furthermore, this categorization seems to lack an adequate level of detail.

Moreover, other taxonomies that use one specific characteristic of the paper (e.g., solution technique), might prohibit the reader from easily finding a paper on a certain topic. For example, when a researcher is interested in finding papers on OR utilization, a taxonomy based on the solution technique does not seem very helpful. We think that the use of descriptive fields avoids these problems.

3 Descriptive Fields

Each field analyzes articles from a different perspective, which can be either problem or technically oriented. In particular, we distinguish between seven fields:

- Patient characteristics (Sect. 3.1): reviewing the literature according to the elective (inpatient, outpatient) or non-elective (urgency, emergency) status of the patient;
- Performance measures (Sect. 3.2): discussing the performance measures (PM) such as utilization, idle time, waiting time, preferences, throughput, financial value, makespan and patient deferral;
- Decision delineation (Sect. 3.3): indicating what type of decision has to be made (date, time, room and capacity) and whether this decision applies to a medical discipline, a surgeon or a patient (type);
- Supporting facilities (Sect. 3.4): discussing whether an approach includes supporting units, e.g., PACU and ICU;
- Uncertainty (Sect. 3.5): indicating to what extent researchers incorporate uncertainty (stochastic versus deterministic approaches);
- Operations research methodology (Sect. 3.6): providing information on the type of analysis that is performed and the solution or evaluation technique that is applied;
- Testing phase (Sect. 3.7): covering the information on the testing (data) of the research and its implementation in practice.

The structure we use is meant to balance between simplicity and comprehensiveness. It provides a simplified, but in our belief for the majority of the readers sufficiently accurate way to identify and select articles they are interested in.

The tables list and categorize all researched articles. Pooling them over the several fields enables the reader to reconstruct the content of a specific paper. They furthermore act as a reference tool to obtain the subset of papers that correspond to a certain characteristic.

Each section clarifies the terminology if needed and includes a brief discussion based on a selection of appropriate articles. Plots are provided for a selection of characteristics to point out the trends set by the research community. It should be noted that the percentages are calculated in relation to the total amount of technical papers. Also note that some fields are not interpretable for some methods and even though rare, some articles contain more than one single method. Moreover, the values for each year in the plots represent the average of the previous, the current and the next year. Using this moving average allows to spot larger research trends in an easier way. After all, a year with fewer publications does not imply that the topic has not been researched in that year.

Finally, in the last part (Sect. 3.8) we go one step further and analyze the connection between different classification fields. This provides insights into research practices.

3.1 Patient Characteristics

Two major patient classes are considered in the literature: elective patients and non-elective patients. The former class represents patients for whom the surgery can be planned in advance, whereas the latter class groups patients for whom a surgery is unexpected and hence needs to be fitted into the schedule on short notice. Although a consistent designation is lacking, a non-elective surgery is considered an emergency if it has to be performed immediately and an urgency if it can be postponed for a short time (i.e., days). As shown in Fig. 2 and Table 3, the literature on elective patient scheduling is vast compared to its non-elective counterpart.

Although many researchers do not indicate what type of elective patients they are considering, some distinguish between inpatients and outpatients. Inpatients are hospitalized patients who have to stay overnight, whereas outpatients typically enter and leave the hospital on the same day.

In reality, there is an ongoing shift of services from inpatient to outpatient care (also called ambulatory care), which is reflected in a higher growth rate of the latter [6, 142, 180]. Moreover, according to the Milliman Medical Index, outpatient expenses increased on average by 9.9% over the years 2009-2013. This increase is largely attributed to increasing prices of existing and more expensive emerging services, but also to a relative increase in outpatient admissions [89, 183].

Compared to an inpatient setting, surgery in an outpatient setting has some particular features. For example, outpatient surgery often consists of more standardized procedures (e.g., routine surgeries, minimally invasive procedures). Moreover, since outpatients are not already present in a hospital ward before surgery, their actual arrival time is uncertain. These and other features might largely impact the choice of the scheduling technique.

Despite the increasing importance of outpatient care in general, the share of articles on outpatient surgery remains flat (Fig. 2).

Besides planning electives, it is also important to consider non-electives. Non-electives can be dealt with in two ways.

Firstly, they can be incorporated in the elective schedule, which usually means that buffer capacity is reserved for them. For instance, van Essen et al. [83] explore the option of break-in-moments. A break-in-moment is the time point when an elective surgery is finished, presenting the opportunity to serve a waiting non-elective patient in the freed-up OR. In their setting, spreading these moments as evenly as possible over the day and ORs lowers non-elective waiting time. ORs are also shared between electives and non-electives in Lamiri et al. [152] who consider several stochastic optimization methods to plan elective surgeries. They present a solution method combining Monte Carlo sampling and mixed integer programming

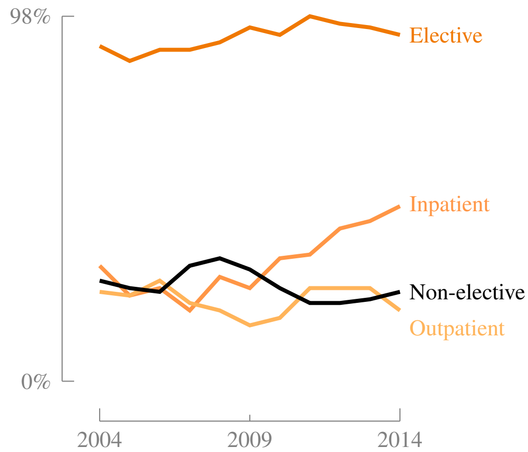

Fig. 2 The majority of articles relate to the elective patient. Contrary to what might be expected, the share of outpatient related articles is not increasing. As some articles deal with both elective and non-elective patients, the sum of both values might add up to more than 100%

(MIP). They also test several heuristic methods from which the most efficient one proved to be tabu search.

Secondly, non-electives can be channeled into dedicated non-elective ORs. This requires however that a constant number of ORs is reserved for them and therefore leaves less free capacity for elective patients. Wullink et al. [272] show that this policy increases the waiting time for non-electives, while Heng and Wright [118] show that this decreases the number of elective cancellations and the amount of OR overtime. Recently, the combined effect of the use of dedicated ORs and a new policy for the urgency classification system is studied by a before-and-after study in [157, 221].

A scenario where a hospital dedicates all of its ORs to emergency services is the case of a disaster. As a consequence, all elective surgeries are cancelled while resources are redirected to provide quick care to non-electives. This type of non-elective patient is an urgency, as quick but not necessarily immediate care is required. Nouaouri et al. [191] sequence a large number of patients resulting from a disaster, with the objective of maximizing patient throughput. Their approach identifies patients that cannot be served by the given hospital and therefore have to be transported to another one.

Recently, Ferrand et al. [96] have researched a setting with a combination of dedicated and flexible ORs and show that it outperforms, in terms of patient waiting time and OR overtime, both the settings with shared ORs as well as the ones

Table 3 The type of patient that is considered in articles is not always specified and, especially for the elective patient case, it is not always clear whether an inpatient or outpatient setting is researched

Elective	
Inpatient	[1, 2, 12, 13, 14, 15, 21, 22, 24, 33, 35, 40, 41, 47, 49, 57, 59, 69, 85, 88, 98, 101, 104, 111, 123, 132, 135, 136, 144, 146, 155, 156, 164, 165, 166, 175, 176, 177, 182, 188, 189, 190, 201, 206, 211, 212, 214, 224, 233, 234, 238, 240, 244, 245, 249, 253, 254, 256, 257, 259, 263, 270, 271, 278, 279, 280, 281]
Outpatient	[13, 15, 23, 25, 35, 41, 44, 45, 62, 69, 70, 71, 77, 81, 88, 97, 101, 103, 107, 108, 111, 123, 125, 130, 136, 144, 146, 156, 159, 175, 176, 177, 188, 189, 190, 206, 213, 218, 223, 235, 238, 239, 240, 249, 254, 259, 264, 278]
Not specified	[3, 4, 7, 9, 10, 11, 16, 19, 34, 38, 39, 52, 55, 56, 58, 61, 63, 64, 67, 68, 74, 78, 83, 84, 87, 90, 91, 92, 93, 94, 95, 96, 100, 102, 109, 113, 114, 115, 116, 117, 119, 124, 126, 129, 131, 138, 139, 140, 143, 145, 148, 149, 150, 151, 152, 153, 154, 160, 168, 169, 170, 173, 174, 181, 184, 185, 186, 187, 192, 194, 195, 197, 198, 200, 202, 203, 204, 205, 209, 215, 216, 217, 222, 226, 227, 228, 236, 241, 242, 243, 246, 247, 251, 252, 260, 261, 268, 269, 272, 273, 274, 276, 277, 282]
Non-elective	
Urgent	[12, 34, 49, 87, 109, 111, 170, 186, 189, 191, 202, 206, 237, 282]
Emergent	[2, 12, 16, 33, 38, 41, 83, 84, 95, 96, 111, 116, 126, 135, 143, 148, 150, 151, 152, 153, 160, 174, 185, 188, 194, 202, 205, 206, 212, 237, 238, 239, 241, 242, 243, 254, 271, 272, 278]
Not specified	[145, 146, 197, 251, 269]
Unclear	[18, 20, 28, 29, 30, 50, 53, 65, 72, 106, 122, 133, 134, 161, 162, 171, 172, 225, 248, 258]

with dedicated ORs. The trade-off between patient waiting time and OR overtime represents the balance between an adequate degree of responsiveness to non-electives and the efficient use of OR resources.

Some authors use more than two urgency classes, i.e., they generalize the two category case of electives and non-electives. The highest urgency category may then be assigned to patients who need immediate care, whereas lower urgency categories can be assigned to patients who can wait for surgery for an extended period of time (e.g., months). For scheduling or evaluation purposes, each urgency category may be assigned a priority score [243] or a surgery target time [259].

An alternative way to categorize surgeries is on the basis of their discipline (e.g., cardiology) and surgery type (e.g., knee surgery or based on the ICD code). Surgery scheduling of different disciplines can to some extent be done independently, as the disciplines are often assigned to separate ORs. This is not the case for surgery types as one OR will typically accommodate more than one type of surgery. However, as a surgery type consists of surgeries that have a similar surgery duration, LOS and resource requirement (e.g., medical equipment), they are often used in models to formulate optimization problems in more general terms than what would be possible at the individual patient level.

For future research, more studies on outpatient surgery are needed. There is already a substantial amount of research on appointment scheduling in outpatient centers, but those results usually rely on modeling assumptions that do not apply to outpatient surgery. Moreover, it should be increasingly a prerequisite to include non-elective arrivals into elective inpatient scheduling models.

3.2 Performance Measures

Different PMs emphasize different priorities and will favor the interests of some stakeholders over others. A hospital administrator could be interested in achieving high utilization levels and low costs, while medical staff might care less about cost factors and rather aim to achieve low overtime. The patient, as the client of the hospital, might care little about the above factors and only desires short waiting times.

Many authors in the scientific community try to find a compromise between the interests of different stakeholders and therefore simultaneously include several PMs. The most common approach is to include a weighted sum of these measures.

We distinguish between the following major PMs: waiting time, utilization, leveling, idle time, throughput, preferences, financial measures, makespan and patient deferral. As shown in Fig. 3, patient waiting time is a frequently used PM. This is understandable as long waiting lists and extensive waits on the day of surgery are common problems in many hospitals. Wachtel and Dexter [266, 267] investigate the increase in waiting time on the day of surgery, for both surgeon and patient, caused by tardiness from scheduled start times.

They conclude that the total duration of preceding cases is an important predictor of tardiness, i.e., the tardiness per case grew larger as the day progressed. A reduction of tardiness can be achieved by modifying the OR schedule to incorporate corrections for both the lateness of first cases of the day and the case duration bias.

Although surgeons are considered to be a valuable resource, their waiting time is included in a surprisingly low number of papers (Table 4). Part of the explanation is related to the fact that waiting time for the surgeon is mostly important in settings that are less frequently discussed in the literature (e.g., a setting where surgeons are allowed to book in any available slot).

We relate underutilization to undertime and overutilization to overtime, although they do not necessarily represent the same concept. Utilization refers to the workload of a resource, whereas undertime or overtime includes some timing aspect. Hence, it is possible to have an underutilized OR, which runs into overtime. In some articles it is unclear which view is applied. Therefore, we group underutilization with undertime and similarly overutilization with overtime.

Fig. 3 shows that minimizing overtime is a popular objective. This is not surprising as overtime results both in the dissatisfaction of the surgical staff and in high costs for the hospital (as higher wages typically apply for the time beyond the normal working hours). Dexter and Macario [75] establish that a correction of systematically underestimated lengths of case durations would not markedly reduce OR overutilization. They came to this conclusion as in their study too few surgeries had a high probability of taking longer than scheduled. Tancrez et al. [241] propose an analytical approach that takes into account both stochastic surgery times and random arrivals of emergency patients. They show how the probability of running into overtime changes as a function of the total number of scheduled surgeries per day. Adan et al. [1] formulate an optimization problem that minimizes the deviation from a targeted utilization level for the OR, the ICU, the medium care unit and the nursing staff. The deviation is measured as the sum of overutilization and underutilization.

For some hospitals, measuring regular OR utilization is important. Interestingly, its use decreased from 2004 on until 2008, but stabilized from then on (Fig. 3). An example where the utilization of the surgical suit is maximized using an integer programming model and an improvement heuristic is provided by Marques et al. [175]. They schedule patients from the waiting list for the next week and assume that overtime is not allowed in the elective schedule. Luangkesorn et al. [163] argue against the use of utilization as a PM and argue that instead congestion metrics such as blocking and diversion should be used.

Fig. 3 also shows that patient throughput is relatively rarely used. It is a quantitative measure, that is usually associated with the amount of patients that is served.

In contrast, preference related measures most often cover some qualitative aspect. They experienced a peak of interest around 2010. Noteworthy is that both in general health care [121] and in the operations research literature value- and quality-based approaches seem to be getting increasingly important. For example, the preferences of cataract surgery patients of one surgeon are investigated by Dexter et al. [76]. The surgeon's patients place a high value on receiving care on the day chosen by them, at a single site, during a single visit and in the morning.

Preferences can also be embodied in patient priorities. Testi et al. [245, 247] define a model where the position of a patient on a waiting list is defined by a priority scoring algorithm, which considers both patient urgency (based on progression of disease, pain or dysfunction and disability) and time spent on the surgical waiting list. Clearly, priority scoring minimizes the total weighted waiting time of all patients. Therefore, an algorithm where patient priorities are equal, will minimize the average patient waiting time.

Including patient priorities drives OR scheduling in a more patient-oriented direction. Min and Yih [184] go one step further and explicitly incorporate an additional factor, namely the cost of OR overtime. In their model, if many high priority patients are on the waiting list, ORs will be kept open longer. This means that the surgery postponement costs are balanced against OR overtime costs. The authors establish that patient prioritization is only useful if the difference between the cost coefficients associated with different priority classes is high, as otherwise a similar schedule can be obtained by using the average postponement cost. Additionally, the relative cost ratio between the cost of patient postponement and OR overtime should not be low, as a low ratio would imply high overtime costs and therefore prioritizing would only marginally affect the surgery schedule.

Table 4 The performance criteria are: waiting time, leveling, utilization related measures, idle time, throughput, preferences (e.g., priority scoring), financial (e.g., maximization of financial contribution per pathology), makespan (completion time), patient deferral/postponement and other (e.g., number of required porter teams)

Waiting time	
Patient	[2, 7, 16, 25, 41, 50, 56, 59, 61, 62, 63, 87, 88, 95, 96, 97, 106, 107, 108, 109, 111, 122, 126, 129, 130, 133, 134, 140, 144, 153, 154, 155, 162, 185, 186, 187, 189, 192, 201, 203, 204, 205, 212, 214, 223, 224, 226, 227, 234, 235, 238, 241, 242, 243, 244, 245, 249, 254, 264, 272, 278]
Surgeon	[19, 52, 61, 63, 154, 168, 211, 259, 264, 279, 280, 281]
Leveling	
OR	[23, 40, 83, 172, 173, 192]
Ward	[21, 22, 24, 40, 47, 84, 85, 98, 113, 164, 165, 195, 222, 240, 256, 257]
PACU	[23, 44, 45, 84, 125, 170, 171, 225, 238, 252]
Patient volume	[169, 192, 240, 243]
Overutilization	
OR	[1, 2, 19, 25, 34, 38, 40, 41, 49, 50, 52, 53, 59, 61, 62, 63, 64, 65, 67, 72, 78, 81, 84, 87, 88, 90, 91, 92, 93, 94, 95, 96, 106, 107, 108, 109, 114, 124, 126, 130, 131, 132, 133, 134, 135, 139, 144, 148, 150, 151, 152, 153, 154, 156, 161, 168, 169, 170, 172, 174, 181, 182, 184, 185, 186, 192, 194, 198, 204, 205, 206, 209, 211, 212, 214, 215, 216, 217, 226, 227, 233, 240, 241, 242, 243, 246, 249, 251, 253, 263, 268, 271, 272, 276, 279]
Ward	[40, 49, 87, 263]
ICU	[1, 2, 59, 135, 198, 263]
PACU	[1, 2, 44, 45, 59, 81, 181]
Underutilization	
OR	[1, 2, 29, 30, 49, 52, 53, 59, 67, 90, 91, 92, 93, 94, 113, 124, 133, 134, 135, 139, 144, 151, 154, 156, 161, 174, 182, 192, 194, 198, 215, 228, 240, 243, 249, 252, 263, 268, 276, 278, 280, 281, 282]
Ward	[263]
ICU	[1, 2, 59, 135, 263]
PACU	[1, 2, 59, 242]
OR idle time	[25, 52, 61, 63, 88, 101, 109, 119, 123, 132, 155, 168, 174, 209, 211, 224, 279, 280, 281]
OR utilization	[7, 13, 15, 16, 20, 33, 34, 35, 41, 50, 55, 67, 69, 87, 95, 96, 97, 103, 114, 116, 136, 144, 153, 154, 165, 175, 176, 177, 192, 205, 226, 235, 238, 243, 246, 249, 251, 259, 272]
Throughput	[7, 13, 14, 15, 16, 20, 33, 40, 103, 116, 117, 136, 144, 156, 174, 176, 177, 182, 190, 191, 213, 222, 226, 235, 243, 246, 254]
Preferences	[3, 4, 14, 24, 28, 38, 44, 45, 55, 58, 77, 84, 104, 135, 145, 152, 164, 184, 185, 187, 197, 198, 201, 202, 214, 223, 236, 237, 240, 244, 245, 246, 247, 259, 260, 261, 269, 277]
Financial	[19, 28, 39, 53, 57, 64, 68, 69, 70, 71, 74, 78, 100, 109, 126, 146, 159, 162, 165, 166, 174, 188, 236, 258, 271]
Makespan	[9, 10, 11, 58, 90, 93, 94, 101, 123, 125, 149, 155, 156, 161, 170, 181, 206, 218, 223, 233, 248, 270, 273, 274]
Deferral/postponement	[2, 12, 34, 41, 53, 57, 59, 81, 84, 87, 102, 116, 119, 140, 143, 144, 160, 203, 204, 205, 212, 226, 238, 239, 246, 282]
Other	[1, 2, 14, 16, 18, 20, 50, 58, 59, 81, 84, 97, 98, 108, 113, 119, 129, 131, 145, 148, 150, 151, 159, 162, 165, 170, 173, 174, 181, 182, 186, 195, 200, 204, 206, 216, 217, 224, 234, 241, 242, 243, 260]

An alternative and increasingly popular perspective on patient prioritization is the use of surgery target/due times (e.g., knee surgeries need to be performed within 2 weeks). Due times can be medically indicated, which entails that certain conditions will get worse if not dealt with in time. They therefore split the patients into various patient priority groups. As the importance of the waiting time for patients between these groups varies largely, a weighted formula can be used. The weight assigned to patients to each group will need to reflect the urgency assigned to that group (e.g., Samudra et al. [220], this weight depends on the maximum allowed waiting time of each due time group). Due times can be set up by the authority of a larger geographic region such as a government [5, 17] or defined by a lower level authority such as a hospital [259].

Next to patient preferences or priorities, surgeon's preferences can be accounted for. As such, Meskens et al. [181] define the affinity between the staff members of the surgical team (i.e., surgeons, nurses and anesthesiologist). By including this measure into a multi-objective optimiza-

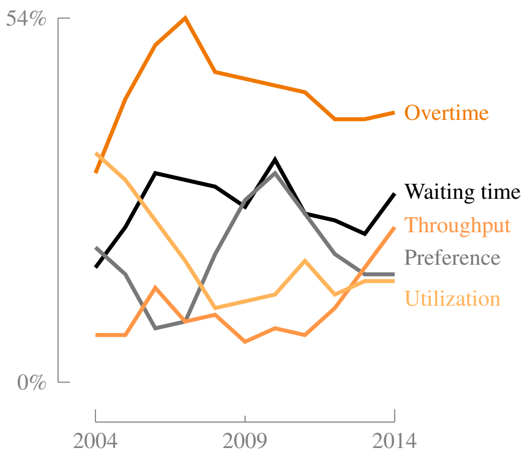

Fig. 3 Overtime, despite experiencing a slight decline, is still the most frequently used performance measure. From 2008 onward, preference-related measures became increasingly popular, followed by a decline in interest after 2010

tion procedure, they try to ensure that team members are working together with their preferred colleagues.

Some authors use purely financial objectives. In Stanciu and Vargas [236], protection levels (i.e., the amount of OR time reserved in a partitioned fashion for each patient class) are used to determine which patients to accept and which to postpone during the planning period under study. A patient class is a combination of the patient reimbursement level and the type of surgery. A patient class enjoys higher priority if its expected revenue per unit surgery time is higher. The goal of the method is to maximize expected revenues incurred by the surgical unit. Patients, given their patient class, are accepted when the protection level for their class can accommodate them. The central question becomes how many requests to accept from low revenue patients and how much capacity to reserve for future high revenue patients.

Financial considerations are also expressed by Wachtel and Dexter [265], who argue that if OR capacity is expanded, it should be assigned to those subspecialties that have the greatest contribution margin per OR hour (i.e., revenue minus variable cost), that have the potential for growth and that have minimal need for a scarce resource such as ICU beds. Furthermore, Wang et al. [271] trade off the cost of opening an OR against the overtime cost for overbooking an OR that is already open. They develop a stochastic model that incorporates uncertain surgery durations, emergency demand and the risk of surgery cancellation.

Lee and Yih [155] minimize the makespan (completion time) of ORs by reducing delays in the patient flow. This is done by determining appropriate surgery starting times. Makespan in general defines the time span between the entrance of the first patient and the finishing time of the last patient in the OR. Since minimizing the makespan often results in a dense schedule, deviations from the plan can result in complications that require adjustments to the schedule. An example is the arrival of a non-elective patient to the hospital.

In the case of a non-elective arrival, it might be necessary to cancel an elective patient, who will consequently be served on a later day. Occasionally, if a non-elective patient cannot be served in a timely manner at the hospital, the deferral of the patient to another hospital can be initiated. General reasons for patient deferrals in one specific hospital are discussed by Argo et al. [8].

The trade-off between unused OR time and the cancellation rate of elective surgeries is investigated by Zonderland et al. [282] using queuing theory. In their setting, electives are canceled because arriving semi-urgencies are fit into the schedule. They also provide a decision support tool that assists the scheduling process of both elective and semi-urgent cases. Herring and Herrmann [119] examine the single-day, single-OR scheduling problem and balance the costs between deferring waiting cases and blocking higher priority cases. They provide threshold-based heuristics for OR managers that allow them to gradually release unused OR time in the days leading up to the day of surgery.

Another way to avoid cancellations is to level the utilization of units supporting the OR. For example, an overutilized PACU can block the OR, therefore prohibiting patients who have already completed surgery from leaving it. A blocked OR will impact succeeding elective surgeries, as they are either delayed or cancelled. This situation can be avoided if the OR schedule is constructed in a way that the utilization of the units supporting the OR is leveled. For instance, Ma and Demeulemeester [164] maximize the number of expected spare beds and investigate bed occupancy levels at wards. The added benefit of leveling the utilization of units supporting the OR is a more balanced workload for the medical staff.

For future work, it could be interesting to increasingly include behavioral factors into the models. For example, a PM representing the satisfaction of staff.

3.3 Decision Delineation

In the literature, various other terms are used to identify typical OR related scheduling problems. Magerlein and Martin [167] distinguish between advance and allocation scheduling. Advance scheduling is the process of fixing a surgery date for a patient, whereas allocation scheduling determines the OR and the starting time or the sequence of the procedures on the planned day of surgery. Within advance scheduling, another distinction can be made between dynamic and static scheduling. In surgery scheduling, dynamic refers to a setting where a patient is given a surgery date at consultation time, whereas in static surgery scheduling the patient is put on a waiting list. Patients on the list are then scheduled at once, e.g., at the end of each week. Dynamic scheduling can be used in settings where waiting lists are rarely used and waiting times are relatively short.

These two problems are handled differently in the literature from a methodological perspective. For the static problem, the hospital can use an algorithm that provides a schedule, i.e., the algorithm substitutes the scheduler. For the dynamic case, the hospital is usually using policies which the scheduler (e.g., assistant of surgeon) should consider in daily practice.

Another common distinction is made between block and open scheduling. In block scheduling, slots or blocks (i.e., a combination of an OR and a day) are typically allocated to a discipline or to a surgeon group. In the subsequent step, surgeons are only allowed to book cases into the blocks assigned to them. The suitability of this approach in various hospital settings is discussed by Van Oostrum et al. [196]. In open scheduling, surgeons are not restricted to a block schedule and can therefore plan surgeries into an arbitrary OR.

In Table 5, we provide a matrix that indicates what type of decisions are examined, such as the assignment of a date (e.g., on Friday, February 25), a time, a room or an amount of capacity. The articles are further categorized according to the decision level they address, i.e., to whom the particular decisions apply. We distinguish between the discipline level (e.g., pediatrics), the surgeon level and the patient level. Papers that are categorized in the column or row with label 'Other' examine a wide variety of aspects. Examples are capacity considerations with regard to beds [160, 225], OR to ward assignment (i.e., $\mathrm{OR_i}$ to $\mathrm{Ward_j}$) [243], patient to week assignments [282] and different timing aspects, such as the amount of recovery time spent within the OR [11].

Using Table 5, problems that target each decision level can easily be identified. The discipline level unites contributions in which decisions are taken for a medical specialty or a department as a whole. Vansteenkiste et al. [259] propose a model to reallocate OR capacity between and within disciplines in such a way that patients are treated within their due time.

At the surgeon level, decisions can involve individual surgeons and also surgeon groups (e.g., all surgeons who perform hip replacement). In Denton et al. [64], surgeries consecutively carried out by one individual surgeon define a surgery block. Surgery blocks are subsequently assigned to ORs. The problem is formulated as a stochastic optimization model that balances the cost of opening an OR with the cost of overtime.

As Table 5 shows, a large part of the literature aims at the patient level. At this level, the decision variables are formulated on the basis of the individual patient or the patient type (e.g., ICD-code).

In Fei et al. [94] patients are scheduled in two stages. In the first stage, patients are assigned to days and rooms, while in the second stage the exact daily sequence (timing aspect) is determined. This is a common way of scheduling patients, as the assignment of the day and the room for a given surgery is easier planned ahead in time than the exact starting time of the surgery, which is often only fixed close to the actual surgery date.

A problem setting where a date and a room (e.g., OR 1, OR of type B) is assigned to patients is discussed by Gomes et al. [103]. Their optimization method includes a component that predicts the duration of surgeries. This is important as the variance in surgery durations has a large impact on OR performance.

Time related decisions can either relate to problems where a sequence (e.g., patient A follows B) or an exact surgery start time (e.g., 2.10 pm) is determined. A method to determine the latter is discussed by Schmid and Doerner [224] who show that it is beneficial to couple routing (e.g., transport from an examination room to the OR) and scheduling decisions.

Capacity related decisions mainly focus on assigning OR time to disciplines, which often results in a cyclic timetable called the MSS. The construction of such an MSS is tested with three dif-

Table 5 The matrix defines the decision (*columns*) and assignment (*rows*) level

	Discipline Level	Surgeon level	Patient level	Other
Date	[14, 15, 21, 29, 30, 39, 40, 50, 53, 56, 68, 98, 109, 122, 169, 222, 226, 245, 246, 256, 257, 278]	[12, 15, 22, 23, 24, 41, 47, 57, 123, 132, 139, 165, 203, 243, 253]	[1, 2, 3, 4, 12, 14, 38, 40, 41, 49, 50, 55, 59, 68, 69, 78, 87, 90, 91, 92, 93, 94, 100, 102, 103, 106, 107, 108, 109, 113, 114, 117, 126, 132, 133, 134, 135, 139, 140, 143, 144, 145, 148, 150, 151, 152, 156, 161, 164, 165, 166, 175, 176, 177, 182, 184, 185, 187, 192, 195, 198, 201, 203, 204, 206, 209, 212, 214, 215, 216, 217, 226, 227, 228, 234, 235, 240, 244, 245, 246, 247, 252, 253, 260, 261, 268, 276, 277]	[57, 78, 85, 87, 165, 244, 263]
Time	[14, 15, 21, 40, 50, 68, 109, 116, 122, 169, 226, 246]	[12, 15, 19, 22, 23, 24, 41, 57, 61, 132, 181, 253]	[3, 9, 10, 11, 12, 14, 19, 25, 40, 41, 44, 45, 50, 61, 62, 63, 65, 68, 78, 81, 84, 88, 90, 93, 94, 96, 101, 103, 107, 109, 115, 116, 117, 125, 129, 130, 131, 132, 133, 134, 145, 149, 153, 154, 155, 161, 168, 170, 171, 173, 175, 176, 177, 181, 182, 191, 206, 211, 214, 216, 217, 223, 224, 226, 233, 239, 246, 248, 253, 261, 270, 273, 274, 279, 280, 281]	[19, 20, 57, 78, 181, 224, 270]
Room	[14, 15, 29, 30, 40, 50, 53, 56, 98, 104, 122, 169, 222, 226, 245, 246, 256, 257, 278]	[15, 19, 23, 24, 47, 57, 64, 123, 132, 139, 165, 181, 203, 243, 253]	[3, 4, 14, 19, 35, 38, 40, 44, 45, 49, 50, 55, 58, 65, 67, 72, 78, 88, 90, 91, 92, 93, 94, 95, 96, 101, 103, 106, 108, 113, 114, 115, 117, 130, 131, 132, 133, 134, 139, 144, 145, 148, 149, 151, 156, 161, 165, 168, 170, 172, 173, 175, 176, 177, 181, 185, 187, 191, 192, 195, 198, 201, 202, 203, 204, 206, 211, 212, 214, 215, 216, 217, 218, 224, 226, 227, 228, 233, 235, 244, 245, 246, 252, 253, 261, 268, 270, 271, 272, 274, 276, 279, 280, 281]	[19, 57, 78, 165, 181, 224, 244, 270, 271]
Capacity	[14, 15, 33, 34, 39, 40, 50, 53, 56, 68, 109, 111, 116, 124, 136, 222, 226, 238, 246, 259, 278]	[15, 19, 28, 41, 52, 57, 61, 70, 71, 74, 139, 146, 165, 181, 203]	[1, 2, 4, 14, 19, 34, 40, 41, 50, 59, 61, 68, 87, 106, 109, 113, 116, 119, 126, 129, 135, 139, 159, 164, 165, 166, 181, 184, 186, 188, 197, 203, 204, 226, 236, 241, 242, 246, 258, 271, 282]	[19, 20, 57, 77, 87, 97, 160, 162, 165, 181, 189, 190, 200, 205, 213, 225, 254, 271]
Other	[251]	[203, 253]	[7, 11, 58, 83, 84, 87, 101, 108, 138, 155, 192, 203, 211, 224, 234, 237, 244, 253, 264, 269, 273, 282]	[77, 87, 224, 244, 249]

For example, articles dealing with the sequencing problem are found in column 3 and row 2 (header rows/columns are excluded). Articles dealing with advance scheduling (assignment step) are found in column 3 and row 1. Allocation scheduling models are generally found in column 3 and rows 2 and 3. Defining patient capacity requirements for a given day of the week are articles found in column 3 and both row 1 and row 4

ferent policies by Cappanera et al. [40] who compare the efficiency (i.e., maximize throughput), the balancing effect (i.e., have a fair allocation of workload for all departments) and the robustness (i.e., prevent disruptions) of the resulting schedule. They also compare the performance of their policies in various hospital settings. Two models are presented by Manmino et al. [169] where, in the first model, OR overtime is minimized and, in the second model, patient queue lengths are balanced amongst different specialties. For the second model they additionally develop a light robustness approach [99] that copes with the demand uncertainty.

Capacity problems can generally be solved in two ways. A hospital can either decide on the number of OR-days to assign to each specialty or, as is proposed by Testi et al. [246] and Adan et al. [2], it can decide on the number of patients it allocates to each OR session. Generally, the division of OR block time is a heavily constrained problem as different factors, such as the available OR block size (e.g., 9 hours), are taken into account. Performance measures that are used to drive such a model are among others the expected costs related to undertime and/or overtime and the number of unscheduled patients [53].

A capacity problem is also discussed by Masursky et al. [178] who forecasted long-term anesthesia and OR workload. They conclude that forecasting future workload should be based on historical and current workload-related data and ad-

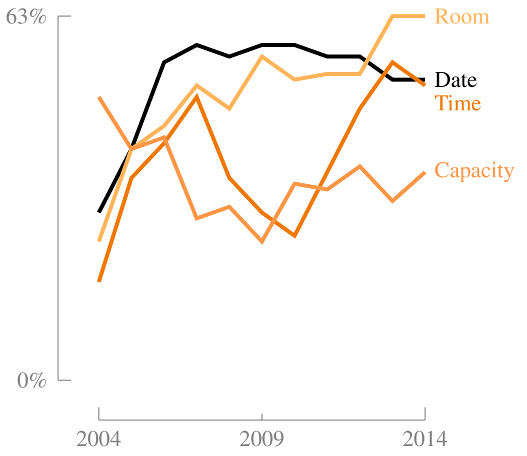

Fig. 4 The assignment of dates and rooms is increasingly popular in the literature, whereas the interest in the time assignment step (e.g., sequencing) shows a more variable pattern, e.g., it has lost some of its popularity around 2010, but regained it towards 2014

vise against using statistical data on the local geographical population. The problem of forecasting workload is also addressed by Gupta et al. [111]. In their case study, simulation is used to answer capacity-related questions. They concluded that a one-time infusion of capacity in the hope to clear backlogs will fail to reduce waiting times permanently, while targeting extra capacity to highest urgency categories reduces all-over waiting times including those of low urgency patients. In situations where arrival rates increased, even if only within a specific urgency class, waiting times increased dramatically and failed to return to the baseline for a long time.

We think that there are two main advantages of identifying papers using the structure of Table 5 over an approach that is based on terminology. Firstly, there will be problem settings that do not have a commonly used term and, secondly, different authors might use the same terminology for variants of the same problem. For instance, Fügener et al. [98] define an MSS as a discipline to date and room assignment, whereas in Banditori et al. [14] it is defined as a patient to date, room and capacity assignment. Table 5 provides therefore a less ambiguous way to identify certain problem settings.

We noted that there are many advanced and complex methods on static surgery scheduling. However, in some hospital settings patients have to be scheduled dynamically, which requires other methods [220]. Therefore, it would be interesting to see more research pointing into that direction. Dynamic scheduling methods are already heavily used in the appointment scheduling literature. The reason they are scarcely used in the surgery scheduling literature is twofold. First, in many hospitals surgeries are scheduled statically, requiring static methods. Second, the methods that are used for dynamic scheduling in an appointment setting are not easily transferable to a surgery scheduling setting for various modeling reasons (e.g., estimated slot durations in the former setting are assumed to be of equal length, while in the latter they are highly variable).

3.4 Supporting facilities

As OR planning and scheduling decisions affect departments throughout the entire hospital, it seems useful to incorporate supporting facilities, such as the ICU or the PACU, in the OR scheduling process and as such to improve their combined performance. When this is ignored, we believe that improving the OR schedule may worsen the efficiency of those related facilities. Whether an article discusses an integrated or an isolated approach can be looked up in Table 6.

The ratio of articles that deal with the OR in an integrated way is staying around the 50% mark throughout the years 2004-2014 (Fig. 5). This is surprising as models are getting more complex and one would expect to observe an increasing interest in integrated approaches. One explanation for this lack of increase is the fact that we exclude articles that do not consider any type of OR planning. Therefore, articles that only deal with a supporting unit, but do not take the OR explicitly into account, are not shown.

As shown in Fig. 5, the problem of the congested PACU received more attention from 2007 onwards. If the PACU is congested, patients are not allowed to enter it and are therefore forced to start their recovery in the OR itself, keeping it blocked. Iser et al. [131] use a simulation model to tackle this problem and compare OR overtime to PACU-specific PMs. Augusto et al. [11] show, using a mathematical model, the benefits of preplanning the exact amount of recovery time a patient will spend in the OR. Generally, as is typical for highly utilized systems, there is a sensitive relationship between overall case volume, capacity (of the PACU) and the effect on waiting time (to enter the PACU). This relationship is described in more detail by Schonmeyr et al. [225] using queuing theory.

Table 6 In an integrated OR, supporting facilities such as the ICU, the PACU and the wards are considered

Isolated OR	[3, 4, 9, 18, 19, 25, 29, 30, 34, 38, 50, 52, 53, 55, 56, 57, 58, 61, 63, 64, 65, 67, 68, 69, 72, 74, 77, 78, 79, 83, 91, 92, 93, 95, 96, 101, 102, 103, 106, 108, 111, 114, 117, 119, 122, 123, 124, 126, 132, 138, 139, 140, 144, 145, 146, 148, 150, 151, 152, 153, 154, 156, 159, 160, 161, 162, 168, 169, 172, 173, 175, 176, 177, 184, 186, 187, 191, 192, 194, 197, 200, 201, 202, 203, 205, 209, 211, 212, 214, 215, 216, 217, 218, 224, 226, 227, 228, 235, 236, 237, 239, 241, 247, 248, 249, 251, 258, 259, 261, 264, 268, 269, 271, 272, 276, 277, 279, 280, 281, 282]
Integrated OR	[1, 2, 7, 10, 11, 12, 13, 14, 15, 16, 20, 21, 22, 23, 24, 28, 33, 35, 39, 40, 41, 44, 45, 47, 49, 59, 62, 70, 71, 81, 84, 85, 87, 88, 90, 94, 97, 98, 100, 104, 107, 109, 113, 115, 116, 125, 129, 130, 131, 133, 134, 135, 136, 143, 149, 155, 164, 165, 166, 170, 171, 174, 181, 182, 185, 188, 189, 190, 195, 198, 204, 206, 213, 222, 223, 225, 233, 234, 238, 240, 242, 243, 244, 245, 246, 252, 253, 254, 256, 257, 260, 263, 270, 273, 274, 278]

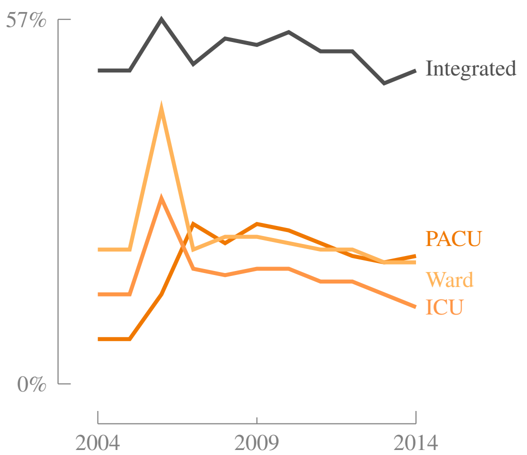

Fig. 5 An integrated OR planning and scheduling process is considered in around 50% of articles. The downstream units (i.e., PACU, ward, ICU) are the most common included supporting units. As only the three main supporting facilities are shown, their count does not necessarily sum up to the total of the integrated approaches

The relationship between the ICU and the OR has been scarcely addressed in the last decade (Fig. 5). Kolker [143] reduces the number of patients served in another than their designated ICU to an acceptable level and defines the maximum number of elective surgeries per day that are allowed to be scheduled along with emergency arrivals. Litvak et al. [160] go a step further and tackle the ICU capacity problem in a cooperative framework. In their model, several hospitals of a region jointly reserve a small number of beds in order to accommodate emergencies and achieve an improved service level for all patients.

Similarly, also the bed management in the wards is closely related to the OR schedule and, in particular, to the MSS. In some hospitals, specialties need to ensure that they have enough capacity in their own wards in order to prevent bed misplacements, unnecessary movements between wards and OR blocking due to bed unavailability. Beliën and Demeulemeester [21] and Vanberkel et al. [256] for instance optimize the MSS in order to level the expected ward occupancy with a mathematical program (MP) and an analytical model respectively. More generally, Fügener et al. [98] propose an MSS that minimizes the cost of downstream units (i.e., capacity costs and staffing costs). The main idea in papers [21, 98, 256] is that based on the MSS, the expected workload in the wards can be calculated. This is the case as the probability distribution of arrival times in downstream units is known. This expected workload can bring possible resource conflicts to light, which then can be corrected by modifying the MSS.

Integrated approaches can also incorporate preoperative units. For example, Huschka et al. [130] consider both an intake and a recovery area as part of a simulation model of an outpatient procedure center. They test several daily scheduling and sequencing heuristics and investigate their impact on the average patient waiting time and the OR overtime. The authors found that these PMs are more influenced by the scheduled arrival time of patients and less by their sequence.

Recently, the integration of the OR schedule with alternative aspects gained attention, e.g., the combination of nurse rostering and OR scheduling [253, 274] and the inclusion of surgery scheduling into a broader perspective of the patient care process [100, 129]. We think that integrating the OR with such alternative aspects is important and we encourage future research on this type of integration.

3.5 Uncertainty

One of the major problems associated with the development of accurate OR planning and scheduling strategies is the uncertainty inherent to surgical services. Deterministic planning and scheduling approaches ignore uncertainty, whereas stochastic approaches explicitly incorpo-

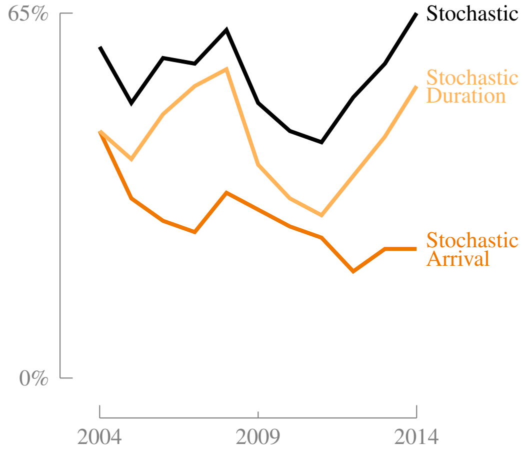

Fig. 6 On average, more than half of the papers take some type of uncertainty into account

Table 7 Stochasticity is frequently taken into account

Deterministic		[3, 4, 10, 11, 12, 15, 18, 22, 23, 28, 29, 30, 39, 44, 45, 49, 50, 55, 57, 58, 70, 72, 77, 78, 79, 81, 84, 90, 91, 92, 93, 94, 95, 97, 100, 101, 103, 106, 115, 117, 124, 125, 129, 131, 132, 133, 134, 135, 139, 145, 146, 149, 159, 161, 166, 169, 173, 175, 176, 177, 181, 187, 188, 191, 192, 197, 198, 201, 203, 206, 211, 214, 215, 216, 217, 218, 222, 224, 233, 234, 235, 240, 244, 245, 247, 248, 252, 253, 256, 257, 259, 260, 261, 263, 270, 273, 274, 276, 277]
Stochastic		
	Arrival	[2, 7, 16, 21, 24, 34, 35, 41, 53, 56, 59, 68, 69, 83, 87, 96, 102, 104, 109, 111, 116, 119, 123, 140, 143, 144, 148, 150, 151, 153, 162, 164, 165, 174, 184, 186, 189, 190, 200, 202, 204, 205, 212, 213, 226, 227, 236, 237, 238, 241, 242, 243, 246, 254, 258, 269, 271, 272, 278, 282]
	Duration	[1, 2, 7, 9, 13, 14, 16, 19, 20, 21, 24, 25, 34, 38, 40, 41, 52, 53, 59, 61, 62, 63, 64, 65, 67, 68, 83, 87, 88, 96, 102, 104, 107, 108, 109, 111, 113, 114, 116, 122, 126, 130, 140, 144, 148, 150, 152, 153, 154, 155, 156, 162, 164, 168, 170, 171, 172, 174, 182, 184, 185, 186, 189, 190, 194, 195, 200, 202, 205, 209, 212, 213, 223, 225, 226, 227, 228, 238, 239, 241, 242, 243, 246, 249, 251, 254, 258, 264, 268, 269, 271, 272, 278, 279, 280, 281]
	Other	[7, 9, 14, 16, 38, 40, 41, 71, 74, 98, 126, 136, 138, 156, 160, 164, 165, 168, 185, 213, 242, 269]

rate it. In Table 7, we classify the articles according to the type of uncertainty that is incorporated.

As shown in Fig. 6, stochasticity in the form of uncertain patient arrivals and surgery durations is frequently incorporated. Non-elective patient arrivals are in most cases impossible to predict in advance and additionally occupy a random amount of OR time, which often leaves OR managers with no option but to reserve capacity for them [241]. In contrast, the arrival of elective patients to ORs contains little uncertainty and is frequently considered as deterministic in the literature. If we narrow down the literature to contributions that explicitly incorporate non-elective patients, we see that around 80% of them use methods that incorporate some sort of uncertainty.

Surgery durations are difficult to predict because for some surgeries the magnitude of the procedure only becomes apparent once the surgery is already in progress. Additionally, the durations often depend on various complex factors, e.g., the characteristics of the patient, the surgeon and the surgical team. As individual surgery durations are uncertain, also their sum, the total workload per OR, is uncertain. Out of all papers, 44% takes duration uncertainty into account, while 28% consider arrival uncertainty.

Duration uncertainty is a central element in Denton et al. [64] as well as in Batun et al. [19]. In Denton et al. [64], decisions include the number of ORs to open and assignments of surgery blocks to ORs, whereas in Batun et al. [19] also the sequence of patients and the starting time of surgeons is determined. Both models aim at minimizing OR opening and OR overtime costs, where Batun et al. [19] additionally consider surgeon idle times. The functional difference between their methods lies in the way surgery to OR assignments are carried out. In Denton et al. [64], the common practice of assigning a surgery block to a single surgeon (block scheduling) is followed, whereas Batun et al. [19] consider the scenario of pooled ORs where surgeons are allowed to switch between ORs. OR pooling allows to carry out surgeries in parallel as the main surgeon only needs to be present during the critical part of the surgery and can move to the next patient before closing the patient.

Shylo et al. [228] introduce a chance-constrained model of overtime that, based on the normal approximation of the sum of durations in one OR-day, provides near-optimal solutions to the surgery to time block assignment problem. Using real data, they show that the developed algorithm is particularly suitable for specialties with high patient volumes per OR-day.

Surgery rescheduling limits the impact that deviations from the initial OR schedule have on the hospital. These deviations on the day of surgery are caused by an uncertain workload due to possible emergency arrivals, deviations from the estimated surgery durations or variable LOS in downstream units. Other causes that can lead to deviations include staff unavailability, equipment failure, late arrival of patients or staff and, in an outpatient setting, patient no-shows. To limit the impact, interventions throughout the day in the form of rescheduling might be needed.

We distinguish between two main types of interventions: cancellations and OR reassignments. In case of an OR reassignment, the patient is still served on the planned day, but is moved or rescheduled to another OR. A more severe intervention is when a patient cannot be served on the planned day and needs to be cancelled. This patient will need to be fitted into the elective schedule of another day. Cancellations are performed throughout the day [80, 220] and can vary considerably from setting to setting (e.g., Leslie et al. [158] (8%), Xue et al. [275] (18%), Epstein and Dexter [80] (11.8%) and Samudra et al. [220] (3.4%)). Many papers report scheduling issues as one of the main causes for case cancellations, next to medical reasons and preoperative or structural reasons [51, 158, 275]. This emphasizes the need for good proactive and reactive scheduling approaches.

An optimization model is proposed by Stuart and Kozan [239] for rescheduling patients on the day of surgery. Their model resequences elective and non-elective patients in each OR whenever a surgery is completed. Using a branch-and-bound algorithm, they maximize the weighted throughput. This implicitly minimizes the patient cancellation rate. Similarly, Erdem et al. [81] reschedule elective patients upon the arrival of an emergency patient. Considering both the OR and the PACU, they minimize the cost of disruptions using a MIP and a genetic algorithm. A decision support system is provided by van Essen et al. [84], where in reaction to disruptions in the schedule adjustments are proposed to the OR manager. An MP is used to derive the decision rules, e.g., either shifting a surgery or scheduling a break between two surgeries.

A method where surgeries are rescheduled across multiple ORs is introduced by Zheng et al. [279]. In their method, at each time point when an OR becomes unoccupied it is determined which surgery to start next. This decision is based on the surgeon's waiting time as well as the OR's idle time and overtime.

It should be clear that operations research techniques are able to deal with stochasticity and especially simulation techniques (used in around 50% of the stochastic literature) and analytical procedures (used in around 20% of the stochastic literature) seem to be well suited. Stochastic programming (e.g., two-stage linear programming) can also be useful to solve these problems. However, there are a limited number of papers that use this technique to solve real-life problems. This constitutes an area for future research.

Studies mostly assume a certain level of variability, based on analyzing historical data, and use this information as input for models. Unfortunately, only limited attention is paid to the reduction of variability within the individual processes. As an example, consider the estimation of surgery durations. Instead of immediately determining the distribution of the surgery durations, one could examine first whether the population of patients for which the durations are taken into account is truly homogeneous. If not, separating the patient population may result in a decreased variability even before the planning and scheduling phase is executed. Since the estimation of surgery durations exceeds the scope of this literature review, we do not elaborate further on this issue. Another example is the reduction of turnover times, as discussed in [141].

Research is needed on applicable rescheduling policies since it is an important mechanism in hospitals which affects both patient and staff satisfaction.

3.6 Operations Research Methodology

The literature on OR planning and scheduling exhibits a wide range of methodologies that fit within the domain of operations research. Table 8 provides an overview of the techniques that are used to solve OR planning and scheduling problems.

In some approaches the impact of specific changes to the problem setting is examined. We refer to such an approach as a scenario analysis since multiple scenarios, settings or options are compared to each other with respect to the PMs. Performing a scenario analysis is popular (Fig.

Table 8 Different solution techniques are used in the literature: analytical procedures (e.g., queueing theory), mathematical programming, dedicated branch-and-bound, scenario analysis (or sensitivity analysis), simulation and various heuristics

Simulation	
Discrete-event	[2, 7, 9, 12, 13, 14, 16, 20, 25, 33, 34, 35, 40, 41, 59, 67, 68, 69, 83, 87, 88, 94, 95, 96, 97, 107, 111, 116, 123, 130, 131, 136, 140, 143, 144, 153, 156, 160, 162, 164, 165, 170, 171, 172, 174, 182, 185, 189, 190, 202, 204, 205, 211, 213, 223, 226, 227, 228, 238, 243, 246, 249, 254, 272, 278]
Monte-Carlo	[34, 62, 71, 114, 148, 150, 152, 154, 185, 186, 192, 200, 281]
Mathematical programming	
Linear programming	[11, 61, 70, 71, 146, 188, 209, 279]
Goal programming	[1, 2, 28, 59, 198, 240]
Integer programming	[3, 29, 30, 38, 44, 47, 50, 53, 57, 77, 84, 85, 103, 119, 132, 165, 166, 191, 195, 215, 222, 223, 235, 243, 244, 245, 246, 258, 280]
Mixed integer programming	[14, 15, 19, 21, 24, 25, 40, 64, 78, 83, 100, 108, 113, 122, 129, 133, 134, 135, 138, 139, 148, 150, 152, 165, 168, 169, 175, 185, 187, 201, 203, 204, 206, 211, 212, 217, 253, 261, 270, 278]
Column generation	[90, 92, 93, 94, 101, 113, 117, 122, 148, 149, 151, 195, 252, 271]
Branch-and-price	[22, 45, 91, 165, 166]
Dynamic programming	[10, 11, 22, 45, 90, 91, 119, 126, 151, 184, 186, 258, 276]
Other	[10, 11, 21, 24, 40, 56, 74, 115, 173, 181, 209]
Improvement heuristic	
Simulated annealing	[21, 24, 49, 62, 83, 85, 98, 114, 152, 153]
Tabu search	[58, 83, 90, 125, 152, 190, 223]
Genetic algorithm	[55, 81, 83, 88, 90, 94, 107, 155, 177, 216, 217, 233, 234, 248, 268, 277]
Other	[29, 30, 53, 56, 63, 83, 88, 98, 114, 148, 151, 152, 153, 172, 175, 176, 185, 214, 215, 224, 228, 236, 273, 274, 276, 280]
Constructive algorithm	[4, 9, 10, 21, 24, 25, 38, 50, 61, 63, 64, 67, 68, 72, 83, 92, 93, 94, 106, 114, 119, 124, 126, 130, 131, 145, 148, 149, 151, 152, 153, 155, 161, 176, 181, 186, 211, 213, 215, 227, 243, 244, 259, 261, 271, 280]
Analytical procedure	[25, 34, 52, 53, 56, 57, 61, 79, 93, 98, 102, 104, 109, 126, 150, 152, 156, 160, 162, 184, 186, 194, 197, 202, 225, 237, 241, 242, 251, 258, 264, 269, 282]
Branch-and-bound	[44, 64, 98, 192, 239, 263]
Scenario analysis	[2, 3, 4, 7, 9, 11, 12, 13, 14, 15, 16, 20, 23, 25, 28, 33, 34, 35, 38, 40, 41, 53, 55, 57, 58, 59, 61, 62, 63, 64, 65, 67, 68, 69, 70, 71, 72, 78, 81, 84, 85, 87, 88, 92, 93, 94, 96, 97, 102, 103, 104, 107, 108, 111, 114, 116, 119, 122, 123, 124, 125, 130, 134, 136, 140, 143, 144, 146, 149, 153, 154, 155, 156, 159, 160, 162, 164, 165, 168, 169, 170, 171, 172, 174, 175, 181, 182, 185, 186, 187, 188, 189, 190, 192, 194, 198, 200, 201, 202, 204, 205, 211, 212, 213, 215, 217, 222, 223, 225, 226, 227, 228, 234, 235, 236, 238, 241, 242, 243, 246, 247, 249, 251, 252, 253, 254, 256, 257, 258, 259, 263, 264, 269, 270, 271, 272, 278, 279, 280]

There are a few papers that are not mentioned in the table as they include a method that could not be clearly assigned to any of these categories

7) and especially in the discrete-event simulation (DES) modeling literature often done.

An integrated DES model is introduced by Steins et al. [238], in which preoperative care and a PACU are considered. The arrival of case types, the surgery time and the LOS in the PACU are represented as probabilistic distributions.

An analytical approach, using a Markov model, is introduced by Tancrez et al. [241] who determine the amount of OR capacity needed to accommodate non-elective patients. Simulation is used to show that the assumptions required to build the Markov chain have a minor influence on their final analytical results. In their work, the stochasticity in OR capacity is the consequence of randomly arriving non-elective patients occupying an uncertain amount of OR time.

Even without non-elective patient arrivals, it might be difficult to predict the required OR capacity on a day, as surgery durations are unknown in advance and can vary considerably in length. Olivares et al. [194] analytically investigate the decision-making process of reserving OR capacity using the newsvendor model. In their approach, an estimate is given of the cost placed by the hospital on having idle capacity and the cost of a schedule overrun. Their results reveal that the hospital under study places more emphasis on the costs of having idle capacity than on the costs of a schedule overrun and long working hours for the staff.

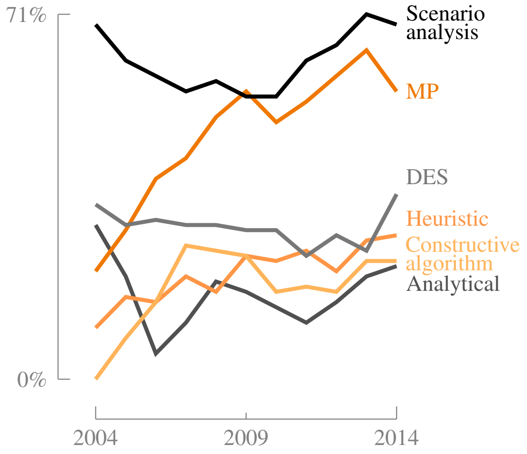

Fig. 7 From the major solution techniques used in the literature only MP experienced a strong growth in popularity

Table 8 shows that MPs, improvement heuristics and constructive algorithms are frequently used. As opposed to DES and analytical models, MPs, such as MIPs, deal with combinatorial optimization problems.

In a large number of cases, the objective function of the optimization model includes under/overtime or under/overutilization. Those PMs are rarely used by themselves, but are usually part of a multi-objective formulation. Over two thirds of MP models use multiple objectives. The popularity of using multiple objectives can be explained in two ways. First, the development of better solvers makes it increasingly practical to use them. Second, defining multiple objectives allows capturing stakeholder preferences more realistically.

In most of the MPs, the decision applies to the elective patient, as in Min and Yih [185]. In their work, a stochastic MIP model is proposed and solved by a sampling-based approach. The surgery durations, the LOS, the availability of a downstream facility and new demand are assumed to be random with known distributions.

In some cases, MPs are too difficult to solve within a reasonable time limit and therefore heuristics are proposed. Fei et al. [93] use a column generation-based heuristic to solve the patient scheduling problem. In their setting, a column corresponds to a feasible plan representing the assignment of surgical cases to an OR. A genetic algorithm is proposed by Roland et al. [217], which determines the assignment of cases to ORs, planning days and operating time periods.

Some of the articles in the literature use methods that have not been covered in the previous paragraphs. Does et al. [79] use Six Sigma to decrease the tardiness of surgeries, which are performed first on a day. Applied to two hospitals in the Netherlands, substantial savings are achieved and the number of surgeries is increased by 10% without requiring additional resources. Epstein and Dexter [66] introduce a method through which analysts can screen for the economic impact of improving first-case starts. First-case starts are also discussed by Pandit et al. [199].

We think that a promising method for future studies is simulation-optimization. This method allows to solve complex optimization tasks, while including the complex features of the OR scheduling process. Also more traditional methods can be used to yield valuable insights. However, the focus should be on making the methods applicable to a broader set of realistic problem settings (e.g., allow multiple sources of variability, broaden the set of supported distributions).

3.7 Testing Phase

Many researchers provide a thorough testing phase in which they illustrate the applicability of their research. Whether applicability points at computational efficiency or at showing to what extent objectives may be realized, a substantial amount of data is desired. From Fig. 8 and Table 9, we notice that most of these data are based on real health care practices. This is noteworthy and results from the improved hospital information systems from which data can be easily extracted.

Investigating the literature, we see that less than 7% of the methods are applied in practice. It seems contradictory that so little research is effectively applied in a domain as practical as OR planning and scheduling.

Unfortunately, simply testing of procedures or tools on real data does not imply that the methods get implemented in real practice. Lagergren [147] indicates that the lack of implementation in the health services seems to have improved considerably. Fig. 8 shows, however, that only a very small share of the articles report on actual implementation. An exception to this is Wachtel and Dexter [264] who introduce a website, which is used by the hospital under study to decide on the exact times patients have to arrive to their surgery appointment. The problem tackled by the authors arises from the fact that a case is often started ear-

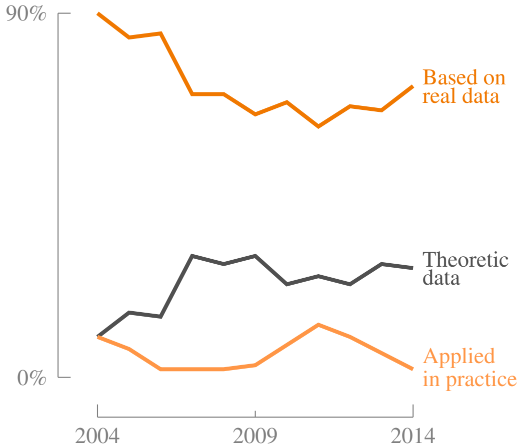

Fig. 8 Even though most data used in the literature are based on real data, it does not mean that the methods are applied in reality

Table 9 For testing purposes, both theoretic and real data are frequently used

Based on real data	[1, 2, 4, 7, 9, 12, 13, 14, 15, 16, 18, 19, 20, 23, 24, 25, 33, 34, 35, 39, 40, 41, 44, 45, 47, 50, 55, 58, 59, 62, 63, 64, 65, 67, 69, 70, 71, 72, 74, 77, 78, 81, 83, 85, 93, 94, 95, 96, 97, 98, 100, 101, 103, 104, 107, 108, 111, 113, 114, 115, 116, 122, 123, 124, 125, 129, 130, 132, 136, 138, 139, 140, 143, 144, 146, 153, 156, 159, 160, 161, 162, 168, 169, 171, 173, 174, 175, 176, 177, 181, 182, 184, 185, 187, 188, 189, 190, 192, 194, 195, 197, 198, 200, 201, 202, 203, 204, 205, 206, 209, 211, 213, 216, 217, 222, 223, 225, 226, 227, 228, 235, 238, 240, 241, 242, 245, 246, 247, 248, 249, 251, 252, 253, 254, 258, 259, 260, 261, 263, 264, 270, 272, 274, 277, 278, 280, 282]
Theoretic data	[10, 11, 21, 22, 38, 49, 52, 53, 56, 61, 68, 72, 87, 90, 91, 92, 102, 106, 109, 117, 119, 126, 131, 133, 134, 135, 145, 148, 149, 150, 151, 152, 154, 155, 164, 165, 166, 170, 172, 186, 191, 192, 212, 214, 215, 224, 233, 234, 236, 237, 239, 244, 268, 269, 271, 273, 276, 279, 281]
Applied in practice	[3, 28, 29, 30, 57, 84, 88, 97, 116, 218, 243, 246, 256, 257]

lier than scheduled, but it cannot be known in advance if it will happen or not. Patient availability must therefore be balanced against patient waiting times and fasting times. Another example is the decision support system of van Essen et al. [84], discussed in Sect. 3.5, for the daily rescheduling problem. Daily applicability is entailed by both methods.

There are problems that have to be solved on a less frequent basis. An example is the application of a case mix model that is applied every year, clearly resulting in a different degree of implementation. A clear comparison of articles on this aspect is hence not straightforward.

Even if the implementation of research can be assumed, authors often provide little detail about the process of implementation. Therefore, we encourage the provision of additional information on the behavioral factors that coincide with the actual implementation. Identifying the causes of failure, or the reasons that lead to success, may be of great value to the research community [43].

A recent example giving insights into these causes is provided by Brailsford et al. [37]. They evaluate the adoption of a particular simulation modeling tool and discuss factors that facilitated or hindered the general adoption of the tool in British health care organizations. Identifying key issues in practice helps the research community to be able to build models that better reflect reality and therefore solve a problem that is closer to the one entailed in practice.

In many articles a problem is defined that is specific to one single hospital and it is unclear whether or to what extent a method is applicable to another setting. In order to justify the generality of their modeling assumptions, Schoenmeyr et al. [225] surveyed several hospitals. Introducing generalizable methods makes it easier to spread and implement good working operations research practices to more than one hospital.

Only limited research has been done to study which planning and scheduling expertise is currently in use in hospitals. Using a survey, Sieber and Leibundgut [229] reported that the state of OR management in Switzerland is far from excellent. A similar more recent exercise for Flemish (Belgium) hospitals is described in Cardoen et al. [46].

We also noticed that few articles build on the results or data of other articles. We therefore think that more reproducible research is needed. One way of achieving this is by publishing the data and models that were used. Making the data publicly available (if allowed by the hospital) also allows to determine whether a method is generalizable.

3.8 Relations between classification fields

So far we looked at classification fields separately. In this section we look at the connections between them (Tables 10, 11 and 11).

In Table 10 we show how much more likely it is to use stochasticity or method (e.g., an analytical method) with a certain field B (e.g., deterministic models) compared to field $\neg B$ (e.g., stochastic models). For example, the table shows that analytical and DES models are often used with similar fields. They are both more likely to be used in stochastic environments where capacity questions have to be answered at the discipline level and non-electives are included. While analytical methods are more likely to be applied to isolated problems and tested with theoretic data, DES methods are more often used in an integrated setting and tested with real data. This is understandable as integrating the OR with a supporting unit will generally make analytical models too complex to solve.

Analytical methods seem to lack the flexibility that would allow them to be used in settings where DES models are usable. Moreover, the fact that they are more often tested with theoretic data suggests that articles using analytical methods are more focused on developing the methodology itself rather than on solving an actual real-life problem.

Table 10 also shows that MP and improvement heuristics are frequently used with similar fields. Both are often applied to deterministic settings that do not include non-elective arrivals. Whereas MPs are used at all decisions levels, improvement heuristics are usually not applied to capacity related decisions.

We noticed that improvement heuristic methods are often applied to problems that are computationally too intensive to be solved by an MP. As larger problems tend to represent real-life settings, one might naturally assume that improvement heuristic methods are used for more realistic problems. Interestingly, this might not necessarily be the case as improvement heuristic methods are, as a matter of fact, more often expected to be tested on theoretic data than MPs (Table 10).

Similarly, constructive algorithms are mostly tested on theoretic data. Generally, they are also applied to isolated settings.

Table 10 also shows results on aspects related to stochasticity. It shows that stochasticity both with regards to arrivals and to surgery durations is mostly applied to discipline and to capacity related problems. Interestingly, stochasticity is less often used in connection with time assignment problems. This is unexpected as one could argue that they represent problems where stochasticity is especially important to consider. Furthermore, problems that include non-electives will often consider both stochastic arrivals and durations. This is positive as non-elective arrival times and their associated added workload are uncertain and are therefore difficult to predict in advance.

Whereas in Table 10 the focus is on methods and stochastic aspects, in Tables 11 and 12 the focus is on PMs and constraints. In Tables 11 and 12 we use a different measure than in Table 10 since we are not interested in the individual importance of a PM/constraint, but in their importance relative to each other. Therefore, we use in Tables 11 and 12 conditional probabilities, while in Table 10 we use ratios of conditional probabilities.

Tables 11 and 12 show among others that the number of considered PMs is usually higher than the number of included constraints. The largest number of PMs are used in DES models. This is understandable as in DES models the number of PMs does generally not determine the run time of the model. This is in contrast to analytical methods where it can be difficult to include many PMs, which might be a problem in a setting, such as surgery scheduling, to which a large amount of competing PMs and constraints are usually inherent.

Table 11 reveals some other interesting connections. For instance, PMs that are mostly used in the DES literature are patient waiting time, overutilization, utilization, throughput and deferral. They are usually used in models that target the discipline level where capacity related decisions are made and in which real data are used for testing purposes. Understandably, deferral is almost exclusively used in settings where arrivals are modeled stochastically.

It is also noteworthy that utilization and makespan, two measures often used in related operations research fields such as machine scheduling [208], are generally less used in the surgery scheduling literature. Instead, authors seem to prefer to use overtime and, to some extent, undertime. Interestingly, when real data are used for testing purposes, the use of overtime is less probable compared to when theoretic data is used.

Criteria that are used as PMs can generally also be used as constraints. For example, instead of minimizing overtime, a constraint can be defined that limits the allowed overtime to a maximum of two hours.

Constraints are included for several reasons. For example, they can be used to represent the limited availability of PACU beds (Supporting Unit), nurses (Personnel) and equipment (Non-personnel). They can also be used to ensure that, e.g., patients are served before a predefined date

Table 10 The likeliness to use stochasticity or method (**C**olumns) with a specific field (**R**ows) compared to using it without the specific field ($\neg R$)

Field	Stochasticity: $\frac{P(C\|R)}{P(C\|\neg R)}$		Method: $\frac{P(C\|R)}{P(C\|\neg R)}$					$P(R)$
	Arrivals	Duration	Analytical	DES	MP	Imprv. heur.	Constr. alg.	
Discipline	1.59	1.15	**1.55**	**1.30**	0.95	0.80	0.70	*.15*
Surgeon	0.69	0.60	0.76	0.64	**1.78**	0.16	**0.93**	*.12*
Patient	0.77	0.97	0.63	0.81	1.29	**1.59**	**2.00**	*.74*
Day	0.88	0.68	0.54	0.67	**1.92**	**1.49**	0.95	*.51*
Time	0.31	0.88	0.28	0.84	1.23	**1.61**	**1.54**	*.39*
Room	0.48	0.61	0.29	0.64	**1.89**	**1.54**	1.53	*.53*
Capacity	2.62	1.31	**2.40**	**1.51**	1.07	0.18	0.79	*.33*
Determ.	0	0	0.16	0.12	**1.48**	**1.13**	0.91	*.46*
Stoch. arriv.	0	2.60	**2.76**	**3.44**	0.64	0.67	1.02	*.28*
Stoch. dur.	5.00	0	**3.33**	**4.17**	0.67	0.86	1.36	*.44*
Theor. data	1.23	0.99	1.52	0.32	1.15	**1.69**	**2.24**	*.27*
Real data	0.79	0.99	0.56	**3.04**	**0.85**	0.58	0.48	*.73*
Non-elective	3.51	1.85	**2.89**	**2.05**	0.72	0.51	0.97	*.25*
Isolated	1.05	1.12	**4.48**	0.53	0.93	1.16	**2.27**	*.56*
Integrated	0.96	0.89	0.22	**1.88**	**1.07**	0.86	0.44	*.44*
$P(C)$	*.28*	*.44*	*.15*	*.30*	*.49*	*.23*	*.21*	

Example: the number for Discipline-Arrivals shows that it is 1.59 times more likely to use stochastic arrivals in making decisions on the discipline level than for decisions on other decision levels. For methods, the two largest numbers for each field are shown in bold

(Preferences) or a minimum number of patients is served by a discipline (Demand).

Understandably, personnel related constraints are particularly often used in models. These allow to include regulations and rules that are important to the hospital management and staff. The table also shows that preference related constraints are often applied.

Overall, Tables 10, 11 and 12 can be used to detect (un)common approaches. We see that the main problem settings all have been researched to some extent already. Consequently, one might wonder whether there is anything left to do in OR planning. The fact that practitioners still see their problems unsolved, suggests that the job of the research community is not yet done. In particular, the community should build upon the findings of previous research to improve the models in a way that they get closer to being usable in reality, e.g., by dropping unrealistic assumptions.

4 Common pitfalls

So far we looked at classification fields and their connections. In this section we go one step further and describe some of the general observations and conclusions we made.

In section 4.1, we discuss how to make a clearer distinction between theory-oriented articles targeting researchers and practice-oriented articles targeting both researchers and practitioners.

In section 4.2 we discuss how some PMs (e.g. overtime) are used universally in articles and why we think more attention has to be paid to selecting setting specific PMs.

In section 4.3 we discuss points that need to be included in each paper in order to make it easier to situate them in the literature and thus classify them. Including those points additionally allows readers to determine in an easier way whether the methods or results described in an article are of interest to them.

In section 4.4 we discuss some of the limitations of this study.

4.1 Clarifying the target group: researchers or practitioners

We think that in the literature a clearer distinction needs to be made between theory-oriented articles targeting researchers and practice-oriented articles targeting both researchers and practitioners (Table 13). We think that because of publishing reasons articles often address both groups, despite the fact that their actual core contribution is usually only

Table 11 Conditional probabilities of various performance measures given different fields

Field	Performance measure: $P(C\|R)$									μ_{Count}	$P(R)$
	Patient waiting	Overutil. OR	Underutil OR	Utiliz. OR	Through-put	Prefe-rence	Finan-cial	Make-span	Defer-ral		
Analytical	**.30**	**.52**	.18	.06	.03	.21	.18	.06	.18	2.30	*.15*
DES	**.48**	**.49**	.18	.40	.29	.09	.08	.09	.25	3.00	*.30*
MP	.24	**.47**	**.25**	.08	.09	.21	.16	.10	.09	2.46	*.49*
Imprv. heur.	**.24**	**.47**	.24	.12	.06	.18	.04	.20	.04	2.12	*.23*
Constr. alg.	**.28**	**.63**	.22	.15	.07	.17	.09	.17	.02	2.37	*.21*
Discipline	.28	**.31**	.16	**.34**	.28	.16	.12	0	.19	2.38	*.15*
Surgeon	.16	**.40**	.12	.16	.08	.08	**.36**	.08	.16	2.32	*.12*
Patient	**.30**	**.52**	.20	.16	.09	.21	.09	.14	.13	2.54	*.74*
Day	.29	**.51**	**.30**	.16	.14	.22	.10	.06	.14	2.59	*.51*
Time	**.26**	**.49**	.12	.16	.15	.13	.06	.24	.11	2.44	*.39*
Room	**.25**	**.53**	.25	.18	.13	.18	.06	.14	.07	2.39	*.53*
Capacity	**.35**	**.39**	.15	.22	.18	.15	.28	.01	.24	2.76	*.33*
Determ.	.17	**.36**	.21	.12	.08	**.24**	.10	.18	.05	2.09	*.46*
Stoch. arriv.	**.47**	**.45**	.15	.30	.18	.15	.17	.02	.32	2.88	*.28*
Stoch. dur.	**.44**	**.59**	.21	.23	.18	.12	.10	.05	.17	2.89	*.44*
Theor. data	**.29**	**.58**	.27	.07	.03	.17	.14	.14	.10	2.42	*.27*
Real data	**.28**	**.40**	.18	.23	.16	.18	.11	.10	.13	2.44	*.73*
Non-elective	**.42**	**.58**	.17	.26	.13	.19	.11	.04	.26	2.77	*.25*
Isolated	**.28**	**.50**	.21	.19	.08	.18	.12	.08	.12	2.20	*.56*
Integrated	**.29**	**.36**	.19	.17	.19	.18	.10	.16	.12	2.69	*.44*
$P(C)$	*28*	*.44*	*.20*	*.18*	*.12*	*.18*	*.12*	*.11*	*.12*		

Example: the value 0.30 represents the conditional probability of the occurrence of patient waiting time given an analytical method. The one but last column shows the average number of PMs used with the specific field. For example, on average 2.30 PMs are used with an analytical model. The two largest numbers for each field are shown in bold

Table 12 Conditional probabilities of various constraints given different fields

Field	Constraint: $P(C\|R)$					μ_{Count}	$P(R)$
	Supp. unit	Personnel	Non-person.	Preferences	Demand		
Analytical	.03	**.24**	.15	**.27**	.09	.88	*.15*
DES	**.18**	**.45**	.09	.18	.15	1.51	*.30*
MP	.26	**.74**	**.36**	.36	.31	2.75	*.49*
Imprv. heur.	.14	**.55**	.14	**.35**	.12	1.65	*.23*
Constr. algo.	.13	**.63**	.26	**.30**	.13	1.78	*.21*
Discipline	.06	**.47**	.22	.28	**.50**	2.09	*.15*
Surgeon	.20	**.76**	.16	.16	**.56**	2.56	*.12*
Patient	.20	**.56**	.24	**.35**	.14	2.03	*.74*
Day	.17	**.71**	.30	**.35**	.32	2.57	*.51*
Time	.25	**.64**	.28	**.40**	.16	2.33	*.39*
Room	.19	**.71**	.29	**.38**	.23	2.40	*.53*
Capacity	.17	**.54**	.21	.17	**.35**	2.06	*.33*
Determ.	.25	**.65**	.31	**.41**	.21	2.59	*.46*
Stoch. arriv.	.12	**.48**	.17	.17	**.20**	1.50	*.28*
Stoch. dur.	.14	**.48**	.14	**.20**	.18	1.48	*.44*
Theor. data	.14	**.54**	.27	**.29**	.14	1.69	*.27*
Real data	.21	**.56**	.20	**.29**	.22	2.08	*.73*
Non-elective	.17	**.40**	.13	**.26**	.13	1.57	*.25*
Isolated	.02	**.53**	.18	**.32**	.13	1.41	*.56*
Integrated	**.41**	**.56**	.27	.24	.28	2.66	*.44*
$P(C)$	*.19*	*.55*	*.22*	*.29*	*.20*		

meant for one of those groups. This carries some risks as it overstates those insights that do not result from the main strengths of the paper. This is a problem for both theory- and practice-oriented articles and could be prevented by having a clear distinction between both types of articles concerning their target group and the resulting conclusions. This would also make it easier for both researchers and practitioners to confidently identify articles that are relevant for them.

The distinction between theory- and practice-oriented articles starts already in the addressed problem and the research task (Table 13). For a theory-oriented paper, the goal is to improve a methodology by solving a specific drawback of it (e.g., an efficient MP that is able to include various sources of uncertainty), while the goal of a practice-oriented paper is to solve a real-life problem (e.g., developing an MP that includes all constraints and PMs that are relevant for the specific real-life problem). As a consequence, for the former, the collaboration with practitioners is not a prerequisite, while it is essential for the latter one.

It can be a problem if theory-oriented articles target practitioners as they might include managerial conclusions which, without understanding the underlying operations research model, might not be interpreted in the right way by practitioners. As these articles mostly focus on a specific method, they will only include those aspects of the real setting that can be implemented using their method and might also, understandably, overemphasize aspects of the real setting that help them to exemplify a certain advantageous property of their method. This way, those aspects that are important in reality, but cannot be included using the chosen model might be left out. Therefore, it might be beneficial if they direct their research towards other researchers and thus make conclusions mainly on methodological aspects. Naturally, they can still report on preliminary insights from a hypothetical case example as these help to guide other researchers to promising areas where the method's real-life applicability can be put to the test.

Similarly, but perhaps to a lesser extent, it is also a problem if authors of practice-oriented articles overemphasize the role of their model adaptations. Clearly, models are often adapted to the real-life problem setting at hand, but generally, those adaptations do not fundamentally improve the methods and therefore will not substantially contribute to the theoretic modeling literature. However, as they can generally choose the most suited method for the problem, they are less restricted by the method's capabilities, which makes it is easier to focus on including aspects that are important in real life.

It is mainly in the conclusion where the lack of a clear distinction might cause problems (Table 13). This is the case for both theory- and practice-oriented articles. For the former this is the case if, e.g., a paper that focuses on a new method mainly concludes on the insights from the testing phase performed on a (perhaps hypothetical) case study. For the latter this is the case if, e.g., a real problem is solved where the conclusion mainly covers adaptations to the model and lacks a clear message that addresses practitioners.

Also the editors of journals can play an important role, since they can ensure that authors are consistent in addressing their target audience (as described in Table 13). Additionally, they also ensure that the audience targeted by these authors coincides with the readers of the particular journal. They can ensure this alignment on the one hand by providing adapted publishing incentives for both theory-oriented and practice-oriented articles and on the other hand by clearly positioning the journal.

4.2 Clarifying the objective

We observed that some PMs (e.g., overtime) are used in articles indifferently of the tackled problem setting (i.e., the combination of a decision and assignment level). In order to better understand how they depend on the problem setting we test their dependency using a Fisher test (Table 14). Unlike the Chi-square test, this test can also be used with low sample sizes.

The results show that 5 out of 9 PMs are not used in a setting specific way. This is surprising, since we would generally expect that for a given problem setting, given PMs apply. Importantly, for this analysis we simplified the problem setting. Although articles often cover more than one decision and assignment level, we will only look at pairs. For example, the assignment of 'patient' to 'day' and 'room' is split into two cases: 'patient' to 'day' and 'patient' to 'room'.

As many PMs are used independently of the problem setting, one might wonder whether PMs are generally used in an appropriate way. We think that this is not always the case and argue that it is important to choose PMs carefully, keeping in mind the following two criteria.

Table 13 A clearer distinction between theory- and practice-oriented articles benefits readers as it makes it easier for them to identify articles that are relevant to them

Theory-oriented	Practice-oriented
The **target group** covers	
researchers	researchers and practitioners *E.g., medical staff, hospital managers, policy makers*
The **addressed problem** is	
an operations research method that has drawbacks limiting its real-life applicability. *E.g., a stochastic dynamic program that is not tractable for patient test sets of realistic size*	a real-life OR planning problem that has no efficient solution yet. *E.g., an inefficient surgery rescheduling policy at a case hospital*
The **research task** involves	
identifying important aspects of the method that need to be improved to ensure real-life applicability. *E.g., aspect that can reduce the dimensionality of the state space in the model formulation*	identifying important aspects of the real setting that need to be included into the model to ensure realism. *E.g., factors that trigger rescheduling such as the arrival of an emergency patient*
identifying approaches that can be used to solve the identified drawbacks. *E.g., aggregate the state space*	identifying methods that can be used to solve the problem at hand. *E.g., an advanced MP approach able to include various personnel constraints*
using objectives and assumptions that are relevant in the context, but are possibly motivated by the literature. This does not require collaboration with practitioners. *E.g., a trade-off between overtime and waiting time, Poisson arrival distribution*	using objectives and assumptions that are realistic and importantly, motivated by the setting. This requires collaboration with practitioners. *E.g., a trade-off between cancellations and overtime, only reschedule to ORs with suitable equipment*
The **findings** include	
the method improvement itself (e.g., relaxation of an assumption). *E.g., the model can now solve datasets with up to 10 ORs, where before this was limited to 5 ORs*	confirming the applicability of a method to the problem at hand. *E.g., the algorithm provides an efficient rescheduling mechanism and has a reasonable running time*
results on the testing phase, which only showcases the capabilities of the improved method using a (hypothetical) example, supported by a scenario analysis. *E.g., based on a hospital with 10 ORs, 7 disciplines and 6 surgery types, the method created an optimal schedule*	results on the testing phase needed to make conclusions. The results are supported by an extensive data analysis. *E.g., the developed policy reduces overtime and the number of cancellations by 10% and 3% respectively*
results on the computational performance of the improved method. *E.g., the model solves all tested scenarios to optimality in less than one hour*	results on the application of the proposed solution (if used in practice). *E.g., adopting the derived decision rules, the staff experienced less overtime and fewer equipment conflicts*
The **conclusions**	
discuss the idea behind the model advancement that led to the beneficial properties of the model. *E.g., aggregating the state space drastically reduces its dimensionality*	discuss the implications the tested decision rules or policies have on the case hospital. For algorithms, they discuss the derived rules or policies. *E.g., analyzing the results of the algorithm showed that rescheduling the patient with the longest duration first results in the best trade-off*
identify promising real-life examples to test the method's applicability. *E.g., the method can now not only solve strategic problems, but also problems that need to be solved daily*	identify promising ways to improve the used method's real-life applicability, i.e., show its limitations. *E.g., once the number of ORs increases, the run time of the algorithm increases drastically*
discuss those insights that can be generalized or used for improvements on other methods. *E.g., Erasing from the memory that part of the state space that will not be used anymore by the algorithm allows to solve problems of realistic size. In other methods this logic of explicitly tagging and erasing data that will not be used anymore can also be used*	discuss those insights that can be generalized or used by other hospitals. *E.g., rescheduling decreases overtime only if OR closing times are flexible and not if they are fixed.* if possible, include comments from practitioners. *E.g., the staff suggests including personnel preferences*

Firstly, the PM should be of practical relevance to the real setting. This means that it is selected in a setting specific way and therefore captures the most important objective(s) of the stakeholders. For example, the average waiting time is an important criteria in many settings. However, if a diverse patient population is assumed, it might not suffice to decrease the average waiting time. For instance, a patient that is waiting for a hip replacement and a patient with metastatic cancer clearly do not exhibit the same urgency. A scheduling method that cuts the average patient waiting time might benefit the former patient category, but seriously harm the latter one.

Secondly, the model needs to contain those mechanisms that principally determine the value of the PM. For example, for a scheduling algorithm in an inpatient setting overtime might not be the most appropriate measure if the model lacks a rescheduling component. This is the case as rescheduling is primarily used to mitigate overtime. Minimizing overtime in a model that does not include rescheduling does not minimize the real overtime of the hospital, but a function that factors into the hospital's cancellation rate. A more realistic model could include a rescheduling component where the cancellation rate is minimized.

Generally, it is a problem if the value of the PM is not principally determined by the tested mechanism. In the best case, the model will rightly show that the PM is not influenced by the tested mechanism, which can be a valuable result on its own. Still, including such a PM will shift the focus away from more important PMs, that did not make it into the model.

In the worst case, the PM will only be dependent on the tested mechanism because of model simplifications (e.g., if deterministic durations are used in open scheduling, surgeon's waiting time is primarily determined by the sequence). In this case, the results derived from the model can suggest benefits that might not be there in reality. Moreover, the implemented mechanisms might worsen the value of other important PMs that were not included in the model.

In order to prevent this problem, the suitability of the PMs to the specific setting should be studied a priory. For example, factor analysis can be used on real data to determine the important factors that determine the value of candidate PMs. It allows to identify the important factors that need to be included in the model in order to get a realistic behavior of the PM (e.g., if the results show that surgery duration uncertainty has a large impact on surgeon waiting time, then optimizing for this PM makes only sense if durations are modeled stochastically). It could also show to what extent the tested mechanism influences the chosen PMs (e.g., whether the sequence of surgeries is amongst the factors that principally determine surgeon's waiting time).

It would be interesting to analyze the connection between problem settings, operations research methods and PMs. This could determine to what extent used PMs are driven by the problem setting (preferred) and to what extent by the method (not preferred), i.e., determine whether PMs are selected because they fit the setting or because they can be used with the chosen method. We tried to uncover these relations using a multiple correspondence analysis. This is a method for decomposing the overall Chi-square statistics, which is similar to decomposing the total variance in Factor Analysis. Unfortunately, this analysis did not yield a result that we could interpret as more than five singular values are needed to only cover 50 % of the inertia (in Factor Analysis terms this corresponds to the variance).

4.3 Clarifying the problem: setting and method specific assumptions

We found it occasionally difficult to classify some articles as the needed information was either difficult to find or simply not included. Making assumptions clearer allows both researchers and practitioners to more easily and reliably determine whether an article is of interest to them.

We distinguish between setting specific (often explicit) and method specific (often implicit) assumptions (Table 15).

Setting specific assumptions are key to understand the (extent of) the problem statement. They generally refer to patient, hospital and problem characteristics (Table 15). With regards to patients, these include, among others, the distribution of surgery durations or the length of stay in supporting units. With regards to the hospital, they mostly cover assumptions on policies and capacity planning, e.g., how many ORs are available for all the surgical disciplines and how are these ORs shared. Finally, with regards to the problem characteristic, they relate, among others, to decisions on whether to incorporate supporting units.

Method specific assumptions directly result from the chosen operations research method. We

Table 14 Selecting appropriate PMs should not be done based on their popularity in the literature

<table>
<tr><th>Setting</th><th colspan="9">Performance measures: observed|expected</th><th>Count</th></tr>
<tr><th></th><th>Patient waiting</th><th>Overutil. OR</th><th>Underutil. OR</th><th>Utiliz. OR</th><th>Through-put</th><th>Prefe-rence</th><th>Finan-cial</th><th>Make-span</th><th>Defer-ral</th><th></th></tr>
<tr><td>Disc-Day</td><td>7|6.3</td><td>7|11.5</td><td>4|4.4</td><td>4|4.6</td><td>6|3.7</td><td>3|3.9</td><td>4|2.8</td><td>0|2.4</td><td>3|3.4</td><td>22</td></tr>
<tr><td>Disc-Time</td><td>4|3.4</td><td>6|6.3</td><td>0|2.4</td><td>5|2.5</td><td>6|2</td><td>2|2.1</td><td>2|1.5</td><td>0|1.3</td><td>3|1.9</td><td>12</td></tr>
<tr><td>Disc-Room</td><td>6|5.4</td><td>6|9.9</td><td>4|3.8</td><td>4|3.9</td><td>6|3.2</td><td>4|3.4</td><td>1|2.4</td><td>0|2.1</td><td>3|3</td><td>19</td></tr>
<tr><td>Disc-Cap</td><td>7|6</td><td>8|11</td><td>3|4.2</td><td>10|4.4</td><td>9|3.6</td><td>3|3.7</td><td>4|2.6</td><td>0|2.3</td><td>6|3.3</td><td>21</td></tr>
<tr><td>Surg-Day</td><td>3|4.3</td><td>5|7.8</td><td>2|3</td><td>4|3.1</td><td>2|2.6</td><td>1|2.7</td><td>2|1.9</td><td>1|1.6</td><td>4|2.3</td><td>15</td></tr>
<tr><td>Surg-Time</td><td>2|3.4</td><td>6|6.3</td><td>0|2.4</td><td>2|2.5</td><td>1|2</td><td>1|2.1</td><td>2|1.5</td><td>1|1.3</td><td>3|1.9</td><td>12</td></tr>
<tr><td>Surg-Room</td><td>2|4.3</td><td>7|7.8</td><td>2|3</td><td>3|3.1</td><td>2|2.6</td><td>1|2.7</td><td>4|1.9</td><td>2|1.6</td><td>2|2.3</td><td>15</td></tr>
<tr><td>Surg-Cap</td><td>3|4.3</td><td>6|7.8</td><td>2|3</td><td>3|3.1</td><td>1|2.6</td><td>1|2.7</td><td>8|1.9</td><td>1|1.6</td><td>3|2.3</td><td>15</td></tr>
<tr><td>Pat-Day</td><td>28|25.2</td><td>53|45.9</td><td>27|17.4</td><td>16|18.3</td><td>12|15</td><td>23|15.6</td><td>8|11.1</td><td>6|9.6</td><td>14|13.7</td><td>88</td></tr>
<tr><td>Pat-Time</td><td>21|21.8</td><td>41|39.7</td><td>10|15.1</td><td>12|15.8</td><td>11|12.9</td><td>10|13.5</td><td>4|9.6</td><td>20|8.3</td><td>8|11.9</td><td>76</td></tr>
<tr><td>Pat-Room</td><td>25|27</td><td>56|49.1</td><td>24|18.6</td><td>18|19.5</td><td>12|16</td><td>19|16.7</td><td>4|11.8</td><td>15|10.3</td><td>6|14.7</td><td>94</td></tr>
<tr><td>Pat-Cap</td><td>15|11.5</td><td>23|20.9</td><td>7|7.9</td><td>8|8.3</td><td>5|6.8</td><td>8|7.1</td><td>1|5</td><td>1|4.4</td><td>12|6.2</td><td>40</td></tr>
<tr><td>p-value</td><td>0.870</td><td>0.116</td><td>0.092</td><td>0.259</td><td>0.007</td><td>0.569</td><td><0.001</td><td>0.001</td><td>0.020</td><td></td></tr>
<tr><td>Count</td><td>123</td><td>224</td><td>85</td><td>89</td><td>73</td><td>76</td><td>54</td><td>47</td><td>67</td><td></td></tr>
</table>

With this contingency table containing PMs and problem settings (here defined as a combination of a decision and an assignment level, see Sect. 3.3) we want to test whether PMs are used in a setting specific way. Each column represents a separate Fisher test on the null-hypothesis that using a PM or not using a PM is equally likely in each setting. E.g., using patient waiting time in a disc-day problem occurred 7 times, but was expected to be observed 6.3 times (=22x123/429). The p-values in bold represent test results where the null-hypothesis cannot be rejected at a 5% significance level, in which cases we conclude that there is no significant relationship between the setting and the use of a specific PM

find it important to emphasize the necessity to include a description of method specific assumptions in articles as we noticed that this is not always the case. This is understandable as for researchers who work with a certain methodology most of the assumptions are always used and consequently they are, in comparison to setting specific assumptions, less consistently reported on. Nevertheless, as they can be difficult to spot by those readers who might have only a limited understanding of the used methodology, we would recommend to highlight them in the text.

There are various assumptions that follow from the chosen method (Table 15). An assumption that is typically made when using an MP or an improvement heuristic to solve the patient-to-date assignment problem is that the patient population that needs to be scheduled is known in advance (i.e., at the moment of scheduling). This assumption is often clearly stated and generally also obvious from the problem formulation.

In contrast, there are assumptions that are less obvious and sometimes not clearly mentioned in the text. One such assumption is that surgeries are restricted from starting before their predetermined surgery start time. By including this assumption, the problem formulation of the MP can be simplified. However, this assumption may not always hold in practice as surgeons may start a surgery right after the preceding surgery is finished (e.g., in a setting where one surgeon performs more than one surgery in sequence). In this setting, a method where the next surgery would necessarily need to be kept on hold until its official start time will give wrong results. Consequently, it is important that practitioners are able to clearly identify articles based on this criterion.

An assumption that is often made in analytical methods (e.g., Markov decision processes) is that surgeries correspond to a certain fixed slot size (e.g., 1 hour). It is important to keep in mind that under this assumption all surgery duration estimates are of equal length. This may hold in some settings, but not in others (e.g., an inpatient setting). Therefore, improvements are introduced to analytical methods that make them more applicable to real settings. For example, Gocgun and Ghate [102] introduce a method that allows to allocate surgeries of various fixed sizes to ORs (e.g., 4 surgeries of 1 hour and 2 of 2 hours).

Generally, we noticed that method based assumptions are more difficult to spot for articles where analytical methods, MP and improvement heuristic are used. In contrast, we found them easier to recognize in articles where DES and constructive algorithms are used as they are methods where a detailed description of the building blocks of the methods is often necessary.

Table 15 Setting and method specific assumptions need to be included in papers on OR planning

Setting specific assumptions	
Patient characteristics	
Patient type	In/outpatient, emergent, urgent
Duration patterns	Distribution (e.g., log-normal, Empirical), mean/variance
Arrival patterns	Distribution (e.g., Poisson, Empirical), mean/variance
Hospital characteristics	
Capacity size	Nr. ORs, nr. beds, equipment, ...
Capacity pattern	Weekly mean/variance, ...
Personnel	Nr. surgeons, medical staff, ...
Hospital type	General, specialized care, ...
Scheduling policy	Dynamic/static, open/block, ...
Same-day policy	Emergency admittance rules,...
Admission policy	Refusal and deferral policy,...
Problem characteristics	
PM	Waiting time, overtime, leveling, ...
Decision level	Discipline, surgeon, patient, ...
Assignment level	Date, time, room, capacity
Supporting units	ICU, PACU, wards, ...
Planning horizon	4 weeks, 6 months, ...
Method specific assumptions	
Surgery durations	Estimated durations are equal (e.g., 1 hour) for all patients (analytical); Deterministic surgery durations (MP, heuristic methods), ...
Arrivals	Poisson arrivals (analytical), ...
Scheduling framework	Patients to schedule are known upfront (MP); Surgery cannot start before scheduled start time (MP), ...

We recommend to mention both setting and method specific assumptions clearly in the text (e.g., in a separate section or table). One way of conveying them in a compact manner is with a classification schema. This idea is already successfully used in queuing theory (Kendall's notation) or machine scheduling (e.g., the three-field notation $\alpha|\beta|\gamma$ [31] describing respectively the machine environment, the job characteristics and the PM). It was first applied to OR scheduling by Cardoen et al. [42]. Future research could focus on expanding this idea.

4.4 Limitations of this review

It can be important for some readers to find articles based on criteria that are not included in this review. For instance, some readers might be interested to identifying articles based on the planning horizon of the scheduling problem (e.g., one week, several months or years), the size of the hospital setting (e.g., number of ORs), or whether the arrivals are assumed to arrive in batches (static scheduling) or one-by-one (dynamic scheduling)

Moreover, this review does not cover classifications on the target group (Sect. 4.2). Information on this aspect is generally not given in articles. Although it can sometimes be inferred from the result section, classifying articles based on this criterion is largely subjective and is best left to the authors themselves.

5 Conclusion

We classified the OR planning and scheduling literature over the years 2000-2014 with regard to the patient type, the different performance measures, the decision that has to be made, the integration of OR supporting units, the incorporation of uncertainty, the operations research methodology and the testing phase. The resulting classification tables enable the reader to quickly identify new relevant articles (Sec. 3.1-3.7). Using the classification fields, we found that

- overtime and patient waiting time are the most used performance measures;
- problems on day and room assignments are more often researched than capacity and timing related problems;
- although stochastic surgery durations are considered in about 44% of the papers, only 28% of the papers consider stochastic arrivals;
- many authors test the developed approach with real data, but only few report on implementation results in practice;
- a classification matrix, showing both the assignment decisions as well as the decision level (Table 5), can help to define the problem characteristics in a less ambiguous way than a terminology based approach.

We also looked at trends for the last ten years and examined connections between the problem setting, the used methods and the performance measures. This showed that

- the amount of published technical articles has been increasing significantly in the recent ten years.
- surprisingly, research on outpatient surgery is not increasing, despite their increasing importance in reality;
- the amount of papers that investigate the OR in an integrated way (e.g., by including the

PACU) is, contrary to what we expected, not increasing;
- MP is the most popular method (included in half of the articles) and its popularity has been increasing over the last ten years;
- analytical and DES models often relate to capacity problems solved at the discipline level. Both generally model the durations and patient arrivals stochastically. DES results, unlike analytical results, are usually tested with real data;
- the number of included performance measures and constraints is the lowest in analytical methods and the highest in DES models;
- most popular constraints are personnel related (e.g., surgeon availability) and preference related (e.g., serve higher priority patient first).

We also found that there are no dominant research trends observable. This shows that the research community is not moving into one particular direction, but instead remains occupied with a wide variety of problems and solutions.

An analysis of the connections between the classification fields showed which approaches, PMs and constraints are commonly combined and which are not (Sec. 3.8). In general, we see that all main problem settings have been researched to some extent already. Consequently, one might wonder whether there is anything left in OR planning. One could argue that OR planning is an outdated research topic and the time has come to focus on other research areas. We think that this argument is flawed as the operations research community did not fulfill its job yet. Results from operations research methods are in the majority of the cases not used in reality because, amongst other things, the models are not realistic enough. We therefore think that getting the currently used methods closer to applicability (e.g., by dropping unrealistic assumptions) remains an open challenge.

In the second part of this article, we identified common pitfalls and points that, based on our analysis of the literature, deserve special attention when researching this field. We found that

- there is a need for a clearer distinction between theoretic articles that contribute advanced methods and applied articles that show the real-life applicability of these methods (Table 13). This distinction would allow articles to focus on their core strengths; Additionally, it would make it easier for both practitioners and researchers to identify articles that are relevant for them;
- many PMs (e.g., overtime) are used in articles indifferently of the tackled problem;
- important information is occasionally missing from articles (Table 15). This makes it harder for readers (especially practitioners) to determine whether the shown research results are relevant to them. For example, generally articles where analytical methods (e.g., Markov models) are used, will often assume estimated durations to be equal, as this is a strong assumption one should be careful when generalizing the results of these methods to inpatient scheduling.

In order to avoid these pitfalls, we conclude that researchers need to

- clearly define the target group (i.e., researchers or practitioners) since this choice impacts all aspects of the research (Sec. 4.1). This also requires adapted publishing incentives;
- choose their performance measures carefully (Sec. 4.2). The most appropriate performance measures for a setting are not necessarily the ones that are the most popular in the literature. In our believe, adequate performance measures should fulfill two criteria. First, they should be of practical relevance to the real setting. Second, the model components that principally drive them should be included. For example, overtime might not be determined by the advance scheduling policy, but rather by how well surgeons estimated their surgery durations. In this case a realistic surgery duration model should be used;
- mention both setting and method specific assumptions clearly in the text (Sec. 4.3), e.g., in a separate section or table. Clarifying method specific assumptions is particularly important since the readers might not always be familiar with the used operations research methods. Spelling out all assumptions helps them to understand whether a method is of relevance to them.

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