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Operating room planning and surgical case scheduling: a review of literature

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Abstract
This paper provides a comprehensive survey of research on operating room planning and scheduling problems. Aiming to give a comprehensive classification on the studied problems, we review the literature from the perspectives of decision level, scheduling strategy, patient characteristics, problem setting, uncertainty, mathematical models, and solutions and methods. The papers are reviewed in diversified ways so as to obtain a detailed overview in this area, and the fields that need to be focused on are summarized. It shows that mathematical programming and heuristics are frequently applied in the complex linear and combinatorial optimization problems. Furthermore, future research trends and directions on operating room planning and scheduling are also identified.

Keywords Operating room · Scheduling problem · Health care management · Combinatorial optimization · Mathematical programming · Literature review

1 Introduction

For most hospitals, the good performance and high efficiency of operating room (OR) plays a crucial role in the improvement of the hospitals benefit and service quality delivered to patients. As stated in many literature, operating theatre is both the cost and revenue centre of a hospital (Macario 2010; Erdogan et al. 2011; May et al. 2011; Cardoen et al. 2010; Macario et al. 1995). More than 60% of hospital admissions are surgical operations (Fügener et al. 2017), which stimulates the hospital managers to

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Table 1 Number of manuscripts in the original set

	1950–1999	2000–2009	2010-Present	Total
Journal	35	83	149	267
Proceedings	3	12	13	28
Working paper	1	4	7	12
Other	5	1	2	8
Total	44	100	171	315

make much effort on the ORs management to improve the planning and scheduling of surgical resources. The performance of operating theatres is largely influenced by the planning and scheduling polices used in practice. Besides the practice of the medical industry, extensive academic research has been conducted in this area (Cardoen et al. 2009a; Wang and Sun 2010; Holguín-Veras et al. 2012; Macario 2010). The process of surgery scheduling involves many participants, such as OR managers, surgeons, and patients. It is very hard to incorporate the requirement of all participants and propose a simple method to improve overall performance of hospital surgical suites. From a mathematical point of view, the problem can be abstracted as a combinatorial optimization model for allocating a given amount of resources considering certain objectives, such as minimizing the operation costs and overtime, maximizing utilization rates of operating room, etc. This problem is very difficult and may become a serious obstacle in hospital management if not solved appropriately.

Until now, there are many review papers that discuss on the ORs scheduling problems (Cardoen et al. 2010; Kim et al. 2014; Hulshof et al. 2012; May et al. 2011). Kim et al. (2014) introduce a research framework for the case mix problem, the master surgery scheduling problem and the surgery scheduling problem. May et al. (2011)organize the literature into six categories: capacity planning, process redesign, the surgical services portfolio, estimation, procedure duration estimation, monitoring, schedule construction, and control. In a recent work, Cardoen et al. (2010) review the literature from 6 perspectives: patient characteristics, performance measures, decision delineation, research methodology, uncertainty and applicability of research. In this paper, we have extended their work by considering more analysis dimensions as well as referring more references.

As already stated, extensive studies have been concluded to solve the combinatorial optimization problems. We searched the databases PubMed, Web of Science, IEEE, Springer and Inspec with respect to related literature. Finally, we acquired a set of 315 papers. More than half of the contributions appeared in or after 2010, which obviously shows the increasing interest of researchers in this field. Table 1 shows the number of manuscripts in the original set.

We organize the literature between six fields:

– Decision levels (Sect. 2): distinguishing between strategic level (long term), tactical level (medium term) and operational level (short term) to better illustrate the problems.

– Scheduling strategies (Sect. 3): concentrating the analysis under block strategy, open strategy or modified block strategy paradigm.
– Patient characteristics (Sect. 4): reviewing the literature according to two classifications, elective or non-elective, and inpatient or outpatient.
– Problem features (Sect. 5): characterizing the problems from the aspects of uncertainty (duration uncertainty, arrival uncertainty, resource uncertainty and care requirement uncertainty), objective functions, certain requirements and multiple stages.
– Mathematical models (Sect. 6): distinguishing between bin-packing model, flow-shop model, stochastic model and bi-criteria model.
– Solutions and methods (Sect. 7): overviewing the solution procedures retrieved from the manuscript set, such as exact algorithms (column generation, dynamic programming, branch-and-bound, branch-and-cut and branch-and-price), heuristics (heuristics based on exact methods, constructive heuristics, improvement heuristics, metaheuristics, linear-programming based heuristics and dispatching-rule based heuristics), simulations and Markov Decision Process.

2 Decision levels

In many literature, the decisions of OR planning and scheduling can be roughly divided into three levels: strategic level for long-term, tactical level for medium-term, and operational level for short-term (Cardoen et al. 2010; Kim et al. 2014; Ma and Demeulemeester 2013; Gupta 2007). At the strategic level, the problems involve medium and long-term demand forecasting and the OR time allocated to medical specialties/surgeons, i.e., capacity planning problem, capacity allocation problem, and case mix problem (CMP). It is a decision process over a relatively long period and higher level. At the tactical level, the problem is related to cyclic OR schedules, i.e. the master surgical scheduling problem (MSSP). At the operational level, the problem is usually the surgery scheduling problem (SSP), to determine the scheduled date, time, and specific required resources allocated to certain surgical cases, including advance scheduling, allocation scheduling, and integration of these two steps. Figure 1 shows the trend of the number of papers in different decision levels. We can find that researchers pay more attention to operational level in recent years.

2.1 Strategic level

Scheduling problems at strategic level consist of capacity planning problem, capacity allocation problem, and case-mix problem (CMP). Generally, the problems have a long planning horizon and are based on highly aggregated information and forecasts. The basic objective on this level is to improve the resource utilization and budget distribution among the shared surgical specialties. The decisions made on the strategic level including the number and specialties of surgeries to be planned, and the number of the resources required, etc., are basically applied in a planning horizon of several months to 1 year or longer (Blake et al. 2002; Wachtel and Dexter 2008).

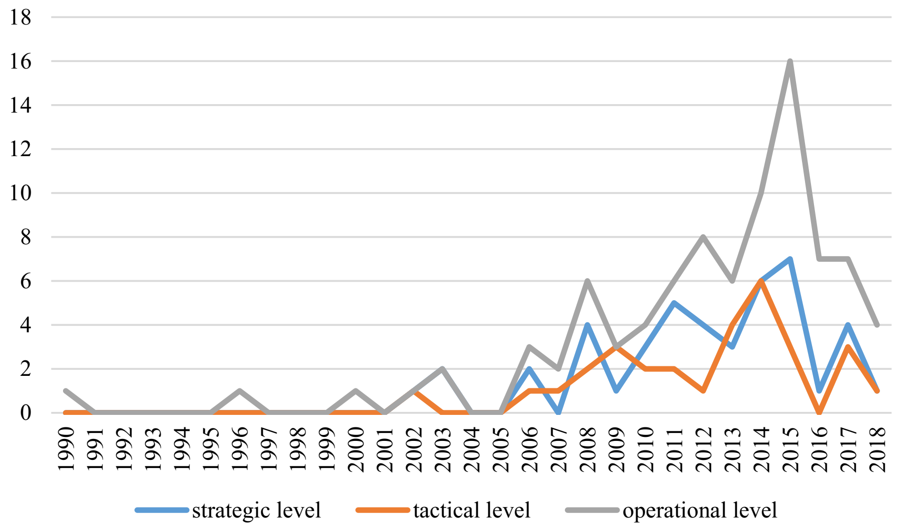

Fig. 1 A tendency chart of the number of papers in different decision levels

There are some papers making the classifications to the different levels of decisions on OR planning and scheduling, for example, Vancroonenburg et al. (2015) incorporate the capacity allocation at tactical level, and Ma and Demeulemeester (2013) combine capacity allocation with case mix at tactical level. However, following most researchers classification method, we classify the capacity planning, capacity allocation, and case-mix problem into the strategic level in this paper. Table 2 lists the papers related to the three problems at strategical level.

2.1.1 Capacity planning

Capacity planning can be described as the process of determining the quantity of resources necessary to meet demands in a cost-effective way (Choi and Wilhelm 2014b). The capacity planning problem is reviewed in a detailed taxonomic classification by many researchers (Lehtonen et al. 2013; Hulshof et al. 2012). From the perspective of resource, OR sessions capacity, namely the OR session length, should match the actual requirement since both under-utilization and over-utilization of an OR are expensive (Agnetis et al. 2014). Inadequate capacity planning can cause low care quality provided by hospitals (Hsu et al. 2003). For example, hospital administrators may have to asses patient admissions over time or route patients to other hospitals if capacity is not sufficient to accommodate them. Hall (2012) considers setting up appointments, distributing medical resources, and planning to ensure that capacity is matched with nursing needs. Following Van Riet and Demeulemeester (2015), Koppka et al. (2018) allow for flexible capacity planning instead of block scheduling, specifically, emergencies are considered as like elective patients in the planning mode, but with uncertain treatment duration and quantity.

Table 2 Procedures at strategic level in the literature

Capacity planning	Koppka et al. (2018), Roshanaei et al. (2017b), Fügener et al. (2017), Penn et al. (2017), Riise et al. (2016), Silva et al. (2015), Dios et al. (2015), Marques and Captivo (2015), Aringhieri et al. (2015b), Choi and Wilhelm (2014b), Agnetis et al. (2014), M'Hallah and Al-Roomi (2014), Lehtonen et al. (2013), Ma and Demeulemeester (2013), Day et al. (2012), Hulshof et al. (2012), Roland et al. (2010), Fei et al. (2009), Lamiri et al. (2008b), Hsu et al. (2003) and Cardoen and Demeulemeester (2008)
Capacity allocation	Koppka et al. (2018), Roshanaei et al. (2017a, b), Vancroonenburg et al. (2015), Choi and Wilhelm (2014a), Creemers et al. (2012), Day et al. (2012), Gul et al. (2011), Tan et al. (2011), Fei et al. (2010), Denton et al. (2010), Lamiri et al. (2008c), Schedule (2006), Guinet and Chaabane (2003), Dexter et al. (2003) and Blake and Carter (2002)
Case-mix problems (CMP)	Koppka et al. (2018), Liang et al. (2015), Castro and Marques (2015), Marques and Captivo (2015), Kim et al. (2014), Vijayakumar et al. (2013), Ma and Demeulemeester (2013), Marques et al. (2012b), Hulshof et al. (2012), Joustra et al. (2011), Guerriero and Guido (2011), Ma et al. (2011), Conforti et al. (2010) and Cardoen et al. (2009a)

2.1.2 Capacity allocation

Capacity allocation refers to the allocation of specialties to operating-room days in OR management. Usually, capacity allocation is prescribed with patient-mix results as a byproduct (Choi and Wilhelm 2014b). Many researchers present their models inspired on the practical problem: how to allocate operating room capacity to various medical disciplines (Creemers et al. 2012; Astaraky and Patrick 2015). Creemers et al. (2012) study the problem of allocating service time slots to different patient classes at strategic, long-term decision level with the objective of minimizing the total expected weighted waiting time of a patient. They analyze a bulk service queueing model for each feasible capacity allocation scheme and present a model that helps OR managers to assess the influence of operating room capacity allocation on waiting time of different categories of patients. Dexter et al. (2003) propose two methods to fill the allocated OR time at different rates. They focus on when and how to release allocated OR time appropriately to maximize OR efficiency. A new case is allowed to replace the previously allocated case that is expected to have the most underutilized OR time on the day of surgery.

2.1.3 Case-mix problems (CMP)

Case-mix planning assigns the OR time blocks among the surgical specialties in a long-term time horizon. This problem involves the number and type of surgical cases that are performed in the ORs (Hulshof et al. 2012). Internal factors include the limited resource capacity. Guido and Conforti (2017) develop a MILPM to determine the case mix planning, including how much OR time is assigned to the different surgeons or surgical groups (Cardoen et al. 2009b). Lehtonen et al. (2013) find that the use of more accurate case categories and their combinations can increase OR productivity. Practically, case combinations that fulfil the reserved OR time should replace less combination that lead to underutilized OR time.

2.2 Tactical level

The problems at tactical level is Master Surgery Scheduling Problem (MSSP). Based on the decisions at strategical level, the tactical problem provide guidelines that facilitate the decisions at operational level.

MSS is a cyclic schedule. It gives the open time of available ORs to surgeons or specialties. It allocates OR time to surgical specialties according to their specific requirements and penalizes undersupply. The time scale is usually monthly or quarterly. MSS determines the workload distribution, which plays an important role in the scheduling process. It is pointed out that capacities of auxiliary departments before or after surgery need to be considered when timing issues arise in MSS (Choi and Wilhelm 2014b). Researchers apply variety of approaches to build MSS. Penn et al. (2017) point out that for medium sized hospitals, it is possible to use a standard MIP solver for the problem of building MSS in a proper amount of time. Beliën and Demeulemeester (2008) use integer programming to match and integrate the construction of MSS with nurse scheduling. The MSS determines the workload distribution, and the revision of the MSS is restricted by the capacity and demand constraint. A feedback could be received from the nurse scheduling process to the surgery scheduling process to produce more equitable MSS. Lehtonen et al. (2013) demonstrate that constructing a more detailed categorization scheme and applying the scheme in constructing MSS can improve the categorized block-scheduling system of the base case. MSS decision is truly a crucial step in the surgery scheduling process between long-term planning at the previous step and case scheduling at the following step. Ma and Demeulemeester (2013) develop a MSS that considers the medium-term decision about resource allocation and take into account the variability and its influence on resource utilizations, such as the expected bed occupancy of each ward. Cardoen et al. (2009a) build a MSS that defines the amount and type of ORs available, the open hours, and the surgeons. It means each surgeon is restricted to operate his or her surgeries in the specific ORs and during the time assigned by the MSS. They use integer programming models and branch-and-bound methodology to solve the surgical case scheduling problem that formulates from practical cases. Guido and Conforti (2017) define a MSS that assigns OR time to surgical specialties and surgeons by optimizing conflicting objectives and at the same time taking into account surgery characteristics and the maximum OR time fixed both for each surgical specialty and surgeon. Agnetis et al. (2014) focus on assigning the different surgical disciplines to the available sessions first and then allocate surgeries to each session to determine the MSS on a weekly basis. They propose a decomposition approach that addresses the MSS problem and the advance surgery scheduling problem. Adan et al. (2009) generate a MSS and optimize an objective function for the utilization of resources to realize a given target of patient throughput by considering the stochastic length of stay on target utilization levels of resources.

More papers on MSS can be found in Koppka et al. (2018), Durán et al. (2017), Vancroonenburg et al. (2015), Aringhieri et al. (2015a), Barbagallo et al. (2015), Kim et al. (2014), Matta et al. (2014), M'Hallah and Al-Roomi (2014), Fügener et al. (2014), Holte and Mannino (2013), Abdelrasol et al. (2013), Agnetis et al. (2012), Editor and Hillier (2011), Tan et al. (2011), Conforti et al. (2010), Tànfani and Testi (2010), Beliën et al. (2009), Testi and Tànfani (2009), Chaabane et al. (2008), Testi et al. (2007) and Blake et al. (2002).

2.3 Operational level

Operational level involves the short-term decision making, namely surgery scheduling problem (SSP) or patient scheduling problem. Following the decisions at tactical level, execution plans at operational level are designed for the matching and scheduling of resources or patients. Surgeries in the waiting list are scheduled to specific OR, day and starting time. Many studies decompose the process of OR scheduling and planning into two steps, namely advance scheduling and allocation scheduling. Advance scheduling is the problem of assigning an OR and a day to each surgery, whereas allocation scheduling determines the starting time of the procedure. Table 3 lists the literature on the advance scheduling, allocation scheduling, and the integration of these two steps.

2.3.1 Advance scheduling

Advance scheduling is also called as intervention assignment or surgical case assignment (Agnetis et al. 2012), mainly used to assign a definite date for each operation. Aringhieri et al. (2015a) study an advance scheduling problem which is about the allocation of OR time blocks to specialties and the subsets of patients to be scheduled within each time block. Day et al. (2012) establish their integrated block-scheduling system (IBS), essentially an advance scheduling system, combining the best aspects of open and block scheduling that are beneficial for both surgeons and hospitals. Besides, some authors also consider the uncertainty in such problems, for example, Beliën and Demeulemeester (2007) present a robust surgery loading study for the advance scheduling problem assuming uncertainty in surgery durations and varying flexibility with respect to a base schedule.

In the advance scheduling problem, the tuple patient-surgeon in the waiting list can shift over a planning horizon of several days (usually weeks). In some cases, some tuples may not be scheduled in the planning horizon. In contrast, in the allocation scheduling problem the assignment of the tuple patient-surgeon to a specific day is under the assumption to have been previously solved, and the problem is to schedule the tuples along the day, usually assuming that operating room overtime may be required at an additional cost (Dios et al. 2015). For example, Dios et al. (2015) present a decision support system that embeds both exact and approximate optimization procedures to solve the surgery advance scheduling problem, while some patient-surgeon tuples may not be scheduled in the planning horizon.

Table 3 Literature on the advance scheduling, allocation scheduling, and the integration of these two steps

Advance scheduling	Al Hasan et al. (2018), Roshanaei et al. (2017b), Turhan and Bilgen (2017), Rachuba and Werners (2017), Ceschia and Schaerf (2016), Jebali and Diabat (2015), Vancroonenburg et al. (2015), Truong (2015), Saadouli et al. (2015), Aringhieri et al. (2015a), Gartner and Kolisch (2014), Marques et al. (2012c), May et al. (2011), Guerriero and Guido (2011), Lamiri et al. (2008b, c), Guinet and Chaabane (2003) and Gerchak et al. (1996)
Allocation scheduling	Kroer et al. (2018), Hamid et al. (2017), Roshanaei et al. (2017a), Latorre-Núñez et al. (2016), van Veen-Berkx et al. (2016), Vancroonenburg et al. (2015), Castro and Marques (2015), Liang et al. (2015), Aringhieri et al. (2015b), Molina-Pariente et al. (2015a), Schmid and Doerner (2014), Wang et al. (2014), Essen et al. (2014), Abdeljaouad et al. (2014), Lee and Yih (2014), Pulido et al. (2014), Niu et al. (2013), Meskens et al. (2013), Lehtonen et al. (2013), Castro and Petrovic (2012), Agnetis et al. (2012), Herring and Herrmann (2012), Dekhici and Khaled (2010), Bilgin et al. (2012), van Essen et al. (2012), Riise and Burke (2011), Souki (2011), Roland et al. (2010), Augusto et al. (2010), Cardoen et al. (2009a, b), Arnaout and Kulbashian (2008), Lamiri et al. (2008a), Wullink et al. (2007), Jebali et al. (2006), Marcon and Dexter (2006), Marcon et al. (2003), Ozkarahan (2000) and Weiss (1990)
Integration of advance scheduling and allocation scheduling	Díaz-lópez et al. (2018), Huang et al. (2018), Moosavi and Ebrahimnejad (2018), Durán et al. (2017), Riise et al. (2016), Landa et al. (2016), Addis et al. (2016), Doulabi et al. (2016a), Marques and Captivo (2015), Marques et al. (2012b, 2014, 2015), Molina-Pariente et al. (2015a), Dios et al. (2015), Van Huele and Vanhoucke (2014), Vijayakumar et al. (2013), Small et al. (2013), Abdelrasol et al. (2013), Riise and Burke (2011), Batun et al. (2011), Fei et al. (2010), Denton et al. (2010), Conforti et al. (2010), Persson and Persson (2009), Perdomo et al. (2008), Pham and Klinkert (2008), Roland et al. (2007), Jebali et al. (2006) and Blake et al. (2002)

2.3.2 Allocation scheduling

Allocation scheduling is also called as intervention scheduling (Ozkarahan 2000) or surgical case scheduling (Cardoen et al. 2009b), which determines the exact start time of the operations and the allocation of the OR resources. The main goal of the scheduling process is to construct a feasible work plan for each surgery day. This is also a process of selecting surgical cases from a waiting list, and possibly pre-assigning them to individual ORs.

Specifically, Vancroonenburg et al. (2015) put forward the allocation scheduling problem following the advance scheduling step, and take it as input for the upcoming planning period. Creemers et al. (2012) identify an optimal allocation scheme by using the output of the bulk service queueing models as the input of an optimization procedure. A step-wise heuristic with a variety of patients and quantities of feasible allocation schemes is proposed. A single-day scheduling problem formulation is first provided by Herring and Herrmann (2012), involving the allocation of a fixed number of resources in the face of demand uncertainty. Wang et al. (2014)consider uncertain surgery duration and emergency demand in an OR allocation problem and formulate a stochastic model to decide the number of open ORs and assignment of each patient to ORs.

2.3.3 Integration of advance scheduling and allocation scheduling

Some studies handle both the advance scheduling problem and the allocation scheduling problem. For example, Marques et al. (2012b) simultaneously consider advance scheduling and allocation scheduling. They allocate elective surgical cases to a certain OR and a specific period of time in a given day along a weekly time horizon with the goal of maximizing the surgical suites utilization. Riise and Burke (2011) state advance scheduling with OR as the only constraint and they also integrate allocation scheduling procedures. More recent studies have broadened the scope of the problem even further, considering the impact of the surgical schedule on downstream resources (Aringhieri et al. 2015b), or integrating with personnel scheduling problems (Van Huele and Vanhoucke 2014). Specifically, Ozkarahan (2000) deal with the allocation of critical resources such as surgeons, nurses, rooms, equipment, and operation time to known individual surgeries. The two processes also all happen on a daily basis. Aringhieri et al. (2015a) tackle simultaneously the master surgery scheduling problem by a tabu search algorithm. The combination of advance and allocation scheduling within a single problem is rarely found in the literature. We leave such detailed problems for further discussion in later sections.

3 Scheduling strategies

Basically, the scheduling problems are studied under three different strategies, i.e., the block strategy, the open strategy, and the modified block strategy (Chaabane et al. 2008; Fei et al. 2009, 2010; Roland et al. 2010; Hulshof et al. 2012; Abdelrasol et al. 2013; Kim et al. 2014; Van Huele and Vanhoucke 2014; Addis et al. 2014; Vancroonenburg et al. 2015). Under a block strategy, the OR scheduling is organized in blocks assigned to specialties. Surgeons are assigned time in a specific OR in a periodic schedule and the corresponding resources are blocked in advance. On the other hand, in an open strategy, all cases can be scheduled into any OR in that appointments may be scheduled with a greater degree of freedom (Denton et al. 2007). A modified block scheduling strategy combines the block and open scheduling strategy, which is flexible and convenient for management. As shown in Table 4, the literature on block scheduling strategy and open scheduling is rather vast compared to the modified scheduling strategy.

3.1 Block scheduling strategy

As mentioned earlier, the block scheduling strategy is to pre-allocates the OR capacity to different surgeons or groups. OR capacity is divided into blocks or slots with each OR for a specified duration. It reduces the complexity of scheduling in that surgeries

Table 4 Literature on different scheduling strategies

Block scheduling strategy	Koppka et al. (2018), Guido and Conforti (2017), Li et al. (2016), Aringhieri et al. (2015a, b), Vancroonenburg et al. (2015), Kim and Mehrotra (2015), Saadouli et al. (2015), Molina-Pariente et al. (2015a), Molina-Pariente et al. (2015b); Marques and Captivo (2015), Agnetis et al. (2014), M'Hallah and Al-Roomi (2014), Meskens et al. (2013), Vijayakumar et al. (2013), Chan and Green (2013), Creemers et al. (2012), Agnetis et al. (2012), Guerriero and Guido (2011), White et al. (2011), Editor and Hillier (2011), May et al. (2011), Zhu (2011), Su et al. (2011), Riise and Burke (2011), Roland et al. (2010), Min and Yih (2010b), Augusto et al. (2010), Beliën et al. (2009), Cayirli and Veral (2009), Lamiri et al. (2008b), Beliën and Demeulemeester (2008), Ozkarahan (1995, 2000)
Open scheduling strategy	Doulabi et al. (2016a), Vancroonenburg et al. (2015), Xiang et al. (2015a), Matta et al. (2014), Marques et al. (2014), Kim et al. (2014), Zhao and Li (2014), Van Huele and Vanhoucke (2014), Peng et al. (2014), Meskens et al. (2013), Marques et al. (2012a, b, c), Liu et al. (2011), Augusto et al. (2010), Fei et al. (2009, 2010), Pham and Klinkert (2008) and Denton et al. (2007)
Modified block schedulig strategy	Molina-Pariente et al. (2015b), Vancroonenburg et al. (2015), Van Huele and Vanhoucke (2014), Roland et al. (2010), Fei et al. (2010), Augusto et al. (2010) and Denton et al. (2007)

can only be allocated to blocks of the particular medical discipline. There are some papers discussing about the time slots allocation in the block scheduling. Lehtonen et al. (2013) notice that there is no difference between using the half-hour and hourly-based divisions in terms of required length of scheduling queue, but using half-hour categorization blocks increases productivity. Creemers et al. (2012) describe a model for allocating server time blocks to patients of various kinds. The capacity of the server is divided into discrete blocks of time. The goal is to minimize the total expected weighted waiting time of patients. Van Veen-Berkx et al. (2016) adjust the block time where the allocated block time can be intentionally extended.

In addition, the block scheduling strategy is often set up based on the resource pre-allocation or the surgeons preferences. Roshanaei et al. (2017b) use a block scheduling system. Under the system, each block of OR is sufficiently equipped with a predetermined number of resources including an anesthesiologist and nurses. During this period, the block is estimated by the charge nurses, according to their previous experience. In some hospitals, block schedules are automatically derived from surgeons preferences (Vijayakumar et al. 2013) or duties, such as clinic, administrative, and educational (Cardoen et al. 2009a, b; Ozkarahan 2000; Testi et al. 2007). In other hospitals, block schedules may be arose by optimization method (Beliën and Demeulemeester 2007).

A large body of literature is based on the block scheduling strategy while relatively fewer studies follow the open scheduling strategy. In practice, the block scheduling strategy is applied more often than the open scheduling strategy in hospitals. Many hospitals in Europe adopt block scheduling, and each surgeon is assigned blocks of time in given ORs (Penn et al. 2017). The surgeons prefer centralizing to scattering their cases at any time of a day, and it is easier to make the schedule since the work time is fixed for each surgeon. However, there are also some drawbacks in the block scheduling strategy. Once a block time of an OR is allocated to one surgeon, other surgeons cannot occupy the block even if that surgeon doesn't arrange any surgical cases in the block time. This problem may be the biggest issue in the opening scheduling strategy. In order to fix the problem, a modified block scheduling strategy is proposed and we will review it in Sect. 3.3.

3.2 Open scheduling strategy

Open scheduling strategy is a more flexible solution in which no pre-specified session-to-discipline assignment exists. Therefore, two cases in different disciplines can be scheduled in the same OR session (Agnetis et al. 2014). Under the open scheduling strategy, surgeons can choose to operate a case on any workday in any available OR, and no surgeons have the priority to reserve any block time in advance. Fei et al. (2009) note that the block scheduling strategy is a special case of the open scheduling strategy since the latter is more flexible than the former. All solutions of the block scheduling strategy are feasible for the open scheduling strategy. Doulabi et al. (2016a) study on integrated OR planning and scheduling at operational level with an open scheduling strategy. They consider the surgeons maximum daily work time, prevent the surgeries operated by the same surgeon from overlapping, allow time for compulsory cleaning when switching from infected cases to non-infected cases, and adhere to the given deadlines. Augusto et al. (2010) focus on the open scheduling strategy, and patients are scheduled without any specialty related restrictions. In addition, Meskens et al. (2013) point out that in block scheduling strategy, ORs are dedicated to a specific specialty. On the contrary, if the managers adopt open scheduling strategy, it will be necessary to distinguish between dedicated rooms and multifunction rooms. Roland et al. (2010) prove that the multifunction of ORs may bring about redundant solutions in the process of solving the scheduling problem.

The open scheduling strategy often follows the scheduling principle of first-come-first-served (FCFS). It is a relaxation of the block scheduling strategy and the utilization rate of ORs under the open scheduling strategy is usually higher than that under the block scheduling strategy. However, because of the flexible arrangements with the stochastic operation time and dynamic patient arrival, it inevitably leads to a long waiting period and other issues. Thus, a poor-designed open system will often cause high loss rate. What's more, patients have priority to choose time can lead to the inconvenience when there is a need to deal with emergency cases. Therefore, open system is proved to be of low utilization and has a lot of delay when compared with block system. In addition, the system is not very popular among surgeons because it brings inconvenience for possibly scattering their working time all over a day.

3.3 Modified block scheduling strategy

Based on the above discussion, we can conclude that the block and open scheduling strategies have their own advantages and disadvantages respectively. Block scheduling is commonly used in application but it is not flexible enough. In an open scheduling strategy, surgeons can use all available time slots in an OR, but it is proved to be inconvenience and the management of such schedules is more difficult. Scholars have increasing interests in studying on the mixture of these two scheduling strategies, which is called modified block scheduling strategy. It enables block scheduling check for underutilization by implementing some policies to modify it. If underutilization of an upcoming OR block is likely to happen, this block may be opened to other surgeons to operate surgical cases. Fei et al. (2009) point out that block scheduling strategy can be modified in two ways. One is to reserve some open time of ORs in advance while the others are left open. Another is to release unused blocks of time at the appointed time. Follow this idea, Fei et al. (2010) adopt a modified block scheduling strategy in which some time blocks are reserved for specific surgeons instead of specialties. They apply some ideas of the open scheduling strategy to surgery planning and scheduling in order to improve the performance in the OR. Denton et al. (2007) establish a model applicable to both block-scheduling and open-scheduling systems. Augusto et al. (2010) modify the block scheduling strategy, which is an intermediate strategy combining the open and block scheduling policies. Molina-Pariente et al. (2015b) use modified block scheduling strategy to solve the OR planning problem of Plastic Surgery and Major Burns Specialty where they assign a date and an OR to a set of surgeries in the waiting list, considering the diverse clinical priority values of patients. These two types of surgeries, which are deferred urgency surgeries, have two reserved OR-days every week because of their unpredictable arrival and high priority, and they can only be operated by a small number of surgeons. Vancroonenburg et al. (2015) assume an open scheduling strategy to tackle the surgical case scheduling problem in which they schedule a set of surgical cases in a set of ORs within a limited scope of planning horizon. Since a schedule confirming to a block scheduling strategy is also suitable for an open scheduling strategy, the method can also be adapted to accommodate block scheduling. In the constraints of the basic problem, they expand availability intervals to accommodate block scheduling.

4 Patient classification

There are two types of classifications of patients in the OR planning and scheduling problems: elective patients or non-elective patients, and inpatients or outpatients. Elective patients are patients whose surgeries will be done over the foreseeable future (typically 1 week) and can be planned in advance. While non-elective patients are group patients whose arrival is unexpected and should be treated as soon as possible. Inpatients refer to the patients who have to stay overnight in hospital, whereas outpatients usually enter and leave the hospital on the same day. Table 5 shows a variety of patients classifications in the literature.

Table 5 Different types of patients in the literature

Inpatients and outpatients	
Inpatients	Aringhieri et al. (2015a), Essen et al. (2014), Marques et al. (2012a, b, c), Tànfani and Testi (2010), Adan et al. (2009), Pham and Klinkert (2008), Derrett et al. (2003) and Guinet and Chaabane (2003)
Outpatients	Kim et al. (2018), Essen et al. (2014), Pham and Klinkert (2008) and Day et al. (2012)
Elective and non-elective patients	
Elective patients	Roshanaei et al. (2017a), Guido and Conforti (2017), Riise et al. (2016), Addis et al. (2016), van Veen-Berkx et al. (2016), Guda et al. (2016), Marques and Captivo (2015), Dios et al. (2015), Molina-Pariente et al. (2015a), Silva et al. (2015), Aringhieri et al. (2015a), Essen et al. (2014), Martinelly et al. (2014), M'Hallah and Al-Roomi (2014), Agnetis et al. (2014), van Essen et al. (2012), Marques et al. (2012a, b, c), Fei et al. (2009, 2010), Min and Yih (2010b), Roland et al. (2010), Cardoen et al. (2009b), Adan et al. (2009), Lamiri et al. (2008b), Derrett et al. (2003), Guinet and Chaabane (2003) and Magerlein and Martin (1978)
Non-elective patients	Duma and Aringhieri (2018), Kroer et al. (2018), Moosavi and Ebrahimnejad (2018), Latorre-Núñez et al. (2016), van Veen-Berkx et al. (2016), van Essen et al. (2012), Tànfani and Testi (2010), Persson and Persson (2010), Zhang et al. (2009), Cardoen and Demeulemeester (2008), Lamiri et al. (2008b), Pham and Klinkert (2008), Vanberkel and Blake (2007), Wullink et al. (2007), Bhattacharyya et al. (2006), Marcon and Dexter (2006), Mulholland et al. (2005), Bowers and Mould (2004), Derrett et al. (2003), Hsu et al. (2003)

4.1 Inpatients and outpatients

Inpatients are admitted to the hospital one or more days before surgery and stay in the hospital after surgery for continuing care, while outpatients usually have same-day surgery and therefore do not stay in hospital overnight (Pham and Klinkert 2008). Many studies have been carried out to improve the efficiency of scheduling in order. Analytical methods and simulation studies have been used to solve the problem of appointment scheduling and planning in healthcare, including inpatients and surgical facilities. Marques et al. (2012c) carry out their research in a general central hospital where maternity or outpatient emergency department are not included.

Outpatients refer to patients who typically enter and leave the hospital on the same day. A typical example of outpatient surgery is ambulatory surgical case. The hospital studied in the work of Day et al. (2012) is one outpatient center owned by the Hospital Corporation of America. Essen et al. (2014) consider both inpatients who must stay in the hospital for a few extra days after surgery and outpatients who are discharged on the day of surgery in the same way.

The difference between inpatients and outpatients scheduling can be summarized as follows: 1. The inpatients can be considered as stand-by while the outpatients dynamically arrive at the hospital with possible lateness, no show or cancel (Aringhieri et al. 2015a; Adan et al. 2009; Fei et al. 2009; Derrett et al. 2003; Guinet and Chaabane 2003; Tànfani and Testi 2010; Marques et al. 2012c; Essen et al. 2014; Day et al. 2012; Kim et al. 2018); 2. The inpatients satisfaction is closely related to the scheduled operation date, while outpatients have lower requirements on it. These features cause the differences in inpatients and outpatients scheduling and thus should be taken into account in the problem (Vissers and Beech 2005; Roland et al. 2010; Liang et al. 2015; Razmi et al. 2015; Wang et al. 2015; Bai et al. 2017).

4.2 Elective and non-elective patients

For surgical patients, they can be classified as elective and non-elective patients. Elective patients do not have to be treated immediately, and therefore they are put in a waiting list. They are called when it is their turn, with just a vague notion of the actual admission moment. Also, they can be given an appointment hospitalization. Elective cases can be planned ahead and have a patient-related cost depending on the surgery date. Non-elective patients are those whose surgeries are unexpected and hence need to be treated urgently. Furthermore, non-elective patients consist of two major patient classes, namely urgent and emergency patients. Urgent patients mean their illness is very serious and need to be admitted immediately but the treatment can be postponed to a certain period. Emergency patients need to be treated at once without lateness.

Though many researchers do not point out explicitly what type of patients they mainly target at, the distinctions between elective and non-elective patients still should be emphasized. One may notice that most papers focus on elective patients and ignore the problems arose in non-elective patients. Compared to non-elective patients, the literature on elective patients planning and scheduling is rather vast.

Elective surgeries can be either conventional or ambulatory (Marques et al. 2014). Conventional surgeries correspond with inpatient surgeries, and ambulatory surgeries correspond with outpatient surgeries. Elective patients are treated within a limited supply of OR blocks, namely sessions. Elective surgery scheduling problem consists of assigning an intervention date, a starting time and an OR for elective surgeries selected from the hospital waiting list (Marques et al. 2015). For most hospitals, the elective cases predominate in the ORs capacity, and because of the limited scheduling space for non-elective patients, most studies in this area are on elective patient scheduling, as can be seen from Table 5.

Non-elective surgery introduces more uncertainty to the problems, in arrival and duration, and the demand for resources during their stay in the hospital. It can be found from Table 5 that there is hardly any research on planning and scheduling for non-elective patients without inclusion of elective patients. Essen et al. (2014) consider the arrival and admission of both elective and non-elective patients when determining a OR-schedule. However, they only consider the expected number of emergency patients, and at the same time, the stochastic nature of the arrival process of emergency patients is not taken into account. Lamiri et al. (2008b) model their problem of OR planning with elective patients and emergent patient, including assigning elective surgeries to different blocks to minimize the expected overtime costs as well as elective cases related costs such as waiting time costs and hospitalization costs. The capacity ability of the OR is shared by two competing patient types: elective patients that need to be planned ahead of time; and emergency patients that must be treated on the day of arrival. Similarly, emergency patients arriving in a certain period of time will be carried out in the same period, regardless of the existing capacity.

Although plenty of studies show that the uncertainty factors such as emergency requirements in OR planning are extremely important, researchers all use the deterministic optimization model in the existing OR planning methods, and the hospital is supposed to use dedicated ORs to serve emergency patients, or to use a fixed portion of the capacity to perform emergency operations (Lamiri et al. 2008b). Wullink et al. (2007) compare two approaches of reserving OR time for emergency surgery. The first approach is reserving the dedicated emergency ORs and an emergency case is operated immediately if the dedicated OR is empty, and in the second approach, an emergency patient is performed once one of the ongoing elective surgeries has ended. A discrete event simulation is used to model the real situation. The results show that emergency patients are operated upon more efficiently on elective ORs instead of a dedicated Emergency OR.

5 Problem features

Based on the features of specific problems, we take the uncertainty, different objective functions, certain requirements and multiple stages as the classifications. In Tables 6 and 7, we list the relevant papers where the surgery durations are stochastic and deterministic respectively with other important features taken into account.

5.1 Uncertainty

The literature on OR scheduling shows that the uncertainty of surgery duration is inherent to surgical services. Clearly, uncertainty is an impacting issue due to the highly variable nature of surgical cases (Vancroonenburg et al. 2015). The consideration of uncertainty in surgery durations and emergency interventions can make the OR scheduling problems quite different from the deterministic ones. Such uncertainty or variability is commonly ignored in many OR planning and scheduling problems which assuming deterministic surgery durations, while stochastic approaches try to incorporate it. In addition to duration uncertainty, the inherent uncertainty in surgeries such as the unforeseen arrival of an emergency patient also has impact on the surgery schedule.

Besides duration uncertainty and arrival uncertainty, some other forms of uncertainty for example on resources and care requirement are also considered by researchers. These topics have obtained increasing attention in the relevant papers. Recent papers which are classified in duration uncertainty, arrival uncertainty, resource uncertainty, and care requirement uncertainty are listed in Table 8. Figure 2 shows the trend of the number of papers in different uncertainty. We can find that duration uncertainty attracts more attention from researchers than other uncertainties in recent years.

Table 6 Papers on surgery scheduling problems with stochastic duration

Publication	Duration	Objective	Method	Type of analysis	Factors
Rath et al. (2017)	$\left[\overline{d_i}-\widehat{d_i},\overline{d_i}+\widehat{d_i}\right]$	$\sum w_i c_i$	A data-driven robust optimization	Approximate	Anesthesiologists; ORs
Guda et al. (2016)	$d \sim N(\mu,\sigma^2)$	$\min\left[\sum_{j+1}^{n}\left[\begin{array}{l} c_w\left(S_j^\pi - A_j^\pi\right)^+ \\ +c_I\left(A_j^\pi - S_{j-1}^\pi - Z_{\pi_{j-1}}\right)^+ \end{array}\right]\right]$	Shortest-Variance-First (SVF) rule	Approximate	Surgeons; ORs
Addis et al. (2016)	$d \sim N(\overline{t_i},{\sigma_i}^2)$	$\min\sum_{i\in I}\left\{\begin{array}{l}\sum_{j\in J}\sum_{k\in K}\left[d_{jk}+\left(w_i+d_{jk}-l_i\right)^+\right] \\ u_i x_{ij}^k+\left[(w_i+D+1)+(w_i+D+1-l_i)^+\right] \\ u_i\left(1-\sum_{j\in J}\sum_{k\in K}x_{ij}^k\right)\end{array}\right\}$	Scheduling-rescheduling framework	Approximate	Total waiting time and tardiness of patients
Dios et al. (2015)	$\ln p \sim N(\mu,\sigma^2)$	$\sum_{p\in P} w_p \sum_{t\in T}\sum_{r\in R}\frac{Z_{prt}}{t}$	A decision support system	Exact and approximate	Material and human resources
Silva et al. (2015)	$d \sim U(1,11)$	$C_{\max}$; $\sum_{s\in S}\sum_{r\in R_s}\sum_{t\in T_s} d_s y_{st}^r$	Relax-and-fix heuristic	Approximate	Human resources
Astaraky and Patrick (2015)	$\ln p \sim N(\mu,\sigma^2)$	$\left(\sum_{p=1}^{P} r_p\varphi_p(i)\right)$	Policy iteration algorithm; dynamic programming methodology	Approximate	The cost of overtime in the OR; cost of exceeding the bed capacity

Table 6 continued

Publication	Duration	Objective	Method	Type of analysis	Factors
Day et al. (2012)	$\{0, 1, 2, \ldots, 100\}$	$\left(\sum_{i \in D} \sum_{k \in K_i} \left[(v_i + \pi_i)\left(u^p_{ik} + u^s_{ik}\right) - h_i \sigma^+_{ik}\right] x_k - c \sum_{j \in B} r_j\right)$	Column generation; Simulation; Benchmark	Approximate	Surgeons; ORs; shared block time
Shylo and Prokopyev (2012)	$d \sim N(\mu, \sigma^2)$	$\min \left\{\sum_{b \in b \setminus b_m} \mathrm{E}\left[\left(l(b) - \sum_{s \in S} d_s x_{s,b}\right)^+\right]\right\}$	An optimization framework; Theoretical properties	Approximate	OR capacity; surgeons; unique piece of equipment; overtime of block
Batun et al. (2011)	Scenarios	$\sum w_i c_i$	Structural properties	Approximate	ORs; surgeons
Denton et al. (2010)	$\underline{d_i} \leq \delta_{ij} \leq \overline{d_i}$	$\min \sum_{j=1}^{m} (c^f x_j + c^v o_j)$	Heuristic	Approximate	ORs; surgeons; nurses

Table 7 Papers on surgery scheduling problems with deterministic duration

Publication	Objective	Method	Type of analysis	Factors
Roshanaei et al. (2017b)	$\min \sum Gu + \sum kx$	Logic-based Benders decomposition (LBBD)approaches	Exact	ORs
Guido and Conforti (2017)	opt $f(x) = [f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)]$	Hybrid genetic solution approach	Exact and meta-heuristic	Surgical specialty; surgical teams
Riise et al. (2016)	$\min \sum_f \alpha_f O^f$	Integration method and sequential method	Exact	Surgeons; ORs; recovery units
Doulabi et al. (2016a)	$C_{\max}$; $\sum_{j \in J} B_j x_j$	A branch-and-price-and-cut algorithm; dominance rules; A fast infeasibility-detection algorithm	Exact	Surgeons; ORs; deadline of surgery
Castro and Marques (2015)	$C_{\max}$; $\sum_{h \in H} \sum_{d \in D} O^h_{h,d}$	Decomposition algorithm	Approximate	Surgeons; specialty; ORs
Marques et al. (2015)	Maximize the number of surgeries scheduled	A weighted Chebyshev distance to a reference point	Approximate	ORs; surgery priority level; specialty
Vijayakumar et al. (2013)	$\sum_{pod} y_{pod} I_{pd}$	A heuristic based on the first fit decreasing algorithm	Approximate	Resource availability; case priorities and variation in surgery times
Meskens et al. (2013)	$C_{\max}$; $\min \begin{bmatrix} \sum_{o=1}^{O} \sum_{r=1}^{R} \sum_{t \geq T_{\text{sup}}}^{T} OTR(o,t,r) \\ \sum_{o=1}^{O} \sum_{b=1}^{B} \sum_{t \geq T_{\text{sup}}}^{T} OTB(o,t,b) \end{bmatrix}$	A generic model	Approximate	Surgeons; nurses; anesthetists
Creemers et al. (2012)	$\min \sum_{y=1}^{Y} w_y z_y^{\max}$	Step-wise heuristic	Approximate	Patient waiting time
Beliën and Demeulemeester (2008)	$\min \sum_{i \in I} \pi_i d_{ik}$	Branch-and-price algorithm	Exact	Nurse; surgeons; ORs

Table 8 Various forms of uncertainty considered in the literature

Duration uncertainty	Koppka et al. (2018), Kroer et al. (2018), Ng et al. (2017), Berg and Denton (2017), Fügener et al. (2017), Rath et al. (2017), Rachuba and Werners (2017), Guda et al. (2016), Addis et al. (2016), Molina-Pariente et al. (2015a), Arcidiacono et al. (2015), Vancroonenburg et al. (2015), Saadouli et al. (2015), Zhang and Xie (2015), Bruni et al. (2015), Addis et al. (2014), Silva et al. (2015), M'Hallah and Al-Roomi (2014), Wang et al. (2014), Cardoen et al. (2009b), Zhang et al. (2014), Sperandio et al. (2014), Choi and Wilhelm (2014b), Lee and Yih (2014), Agnetis et al. (2014), Guo et al. (2014), Lehtonen et al. (2013), Shylo et al. (2013), Erdogan and Denton (2013), Kong et al. (2013), Herring and Herrmann (2012), Choi and Wilhelm (2012), Day et al. (2012), Gul et al. (2011), Batun et al. (2011), Persson and Persson (2010), Min and Yih (2010b), Denton et al. (2010), Valls et al. (2009), Cardoen and Demeulemeester (2008), Chaabane et al. (2008), Denton et al. (2007) and Beliën and Demeulemeester (2007)
Arrival uncertainty	Kroer et al. (2018), Rachuba and Werners (2017), Latorre-Núñez et al. (2016), Guda et al. (2016), Barz and Rajaram (2015), Astaraky and Patrick (2015), Xiang et al. (2015a), Ferrand et al. (2014), Zhang et al. (2014), Holte and Mannino (2013), Day et al. (2012), Min and Yih (2010a), Persson and Persson (2010), Denton et al. (2010), Cardoen et al. (2009a, b), Cardoen and Demeulemeester (2008) and Punnakitikashem et al. (2008)
Resource uncertainty	Doulabi et al. (2016a), Marques et al. (2015), Vancroonenburg et al. (2015), Kim and Mehrotra (2015), Marques and Captivo (2015), Molina-Pariente et al. (2015a, b), Saadouli et al. (2015), M'Hallah and Al-Roomi (2014), Zhao and Li (2014), Vijayakumar et al. (2013), Holte and Mannino (2013), Chan and Green (2013), Editor and Hillier (2011), Cardoen (2011), Su et al. (2011), Gul et al. (2011), Riise and Burke (2011), Min and Yih (2010b), Cardoen et al. (2009b), Valente et al. (2009), Cardoen and Demeulemeester (2008), Lamiri et al. (2007), Jebali et al. (2006), Lebowitz (2003), Hsu et al. (2003), Ozkarahan (1995, 2000) and Macario et al. (1995)
Care requirement uncertainty	Guo et al. (2016), Barz and Rajaram (2015), Guo et al. (2014), Aij et al. (2014), Martinelly et al. (2014), Yahia et al. (2014), Matta et al. (2014), Holte and Mannino (2013), Lim et al. (2012), Punnakitikashem et al. (2008), Belien and Demeulemeester (2005); Beliën and Demeulemeester (2008), Bolduc (1996) and Stull (1991)

5.1.1 Duration uncertainty

Surgery duration refers to the processing time of the surgery. Duration uncertainty refers to the deviations between the actual and the planned durations of relevant activities during the surgical process. The uncertainty of surgery duration is mainly caused by the patient condition, the skill of the surgeon and any other factors that can make the surgery smooth or not (Molina-Pariente et al. 2015a). Furthermore, the duration depends on the surgical specialty such as orthopedic, cardiac, or neurological. Uncer-

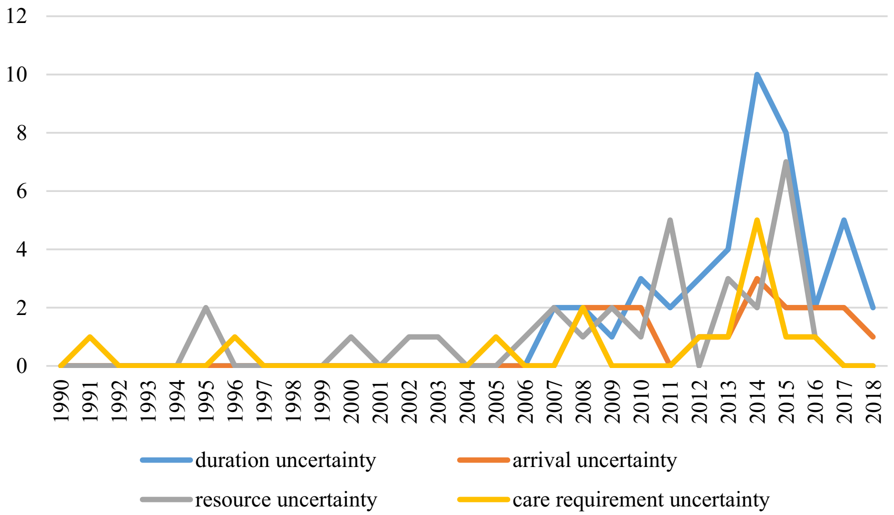

Fig. 2 A tendency chart of the number of papers in different uncertainties

tain actual surgery duration is a significant factor in surgery planning and scheduling problems, which makes the problems much more challenging. Some researchers incorporate induction and waking up time in surgery duration since these procedures are also performed in the OR (Saadouli et al. 2015; Fei et al. 2010). How to model the stochasticity of surgery durations is a key factor in practice, and the assumptions on surgery duration distributions have great effect on the resulted overtime and idle time of the ORs (Guda et al. 2016). The researchers either assume that the duration of operation is a random probability distribution, or use Monte Carlo simulation (Zhu 2011). Three distributions are often used to model the surgery duration, i.e., the lognormal, gamma, and normal. In some cases, researchers predict the surgery duration for each procedure individually, and assign the starting time based on the desired sequencing rule. For example, Rath et al. (2017) develop a two-stage, mixed-integer stochastic dynamic programming model using a data-driven robust optimization method. The resources are allocated to elective surgeries with uncertain durations and the sequence of surgeries is prescribed. Lehtonen et al. (2013) use duration categories in case scheduling to improve OR productivity. They develop a practical scheduling system at the department of orthopedic through detailed analysis of surgery durations, considering the advantages of both surgery categorization and newsvendor model to surgery scheduling. To hedge against the uncertainty in surgery durations, researchers adopt variety of methods (Beliën and Demeulemeester 2007; Vancroonenburg et al. 2015; Zhu 2011; Denton et al. 2007, 2010; M'Hallah and Al-Roomi 2014). Denton et al. (2007) establish a stochastic optimization model and some practical heuristics to compute OR schedules, which hedges against the uncertainty in duration. Zhu (2011)extend their research into the dynamic scheduling with uncertain operation execution time using a two-stage scheduling approach of ORs by a MIP and a multi-agent system.

5.1.2 Arrival uncertainty

Arrival uncertainty refers to the unpredictable arrival of outpatients at the start of the surgery operation. Researchers explore variable approaches to address the stochastic problem about arrival (Min and Yih 2010a; Cardoen et al. 2009b, a). As one hand of the relevance, allowing ample time to get into the hospital decreases the probability to arrive late as a result of traffic uncertainty (Cardoen et al. 2009b). Min and Yih (2010b) provide a stochastic approach to the advance scheduling problem which considers the uncertainty on surgery durations, emergency arrivals and the length of stay in the ICU. Cardoen et al. (2009a) suggest that patients have a substantial trip distance after a certain reference period. When these patients have more time to manage the travel, they are more satisfied while there is less chance to arrive late at the hospital. Persson and Persson (2010) use a discrete-event simulation to study the OR planning problem at orthopaedic department, considering both uncertainty of patient arrival and operation execution time. They use a discrete-event model to study how different management policies affect different performance indicators and propose a scenario that is well enough to meet the demand of uncertainty.

5.1.3 Resource uncertainty

In hospitals, balancing the operational costs and the service level is hard. In the problems of OR planning and scheduling, the constraints are mainly about the availability, applicability, and usability of resources, including human resources and material resources. A set of resource combination is open to certain cases on certain time in certain place, while others may be unavailable or inapplicable. Only few researchers pay attention to resource uncertainty. Assuming that some facility breaks down in the OR before the surgery or when the surgery is still under way, it would lead to postpone of the surgery until the facility is accessible again (Cardoen and Demeulemeester 2008). We should note that resource uncertainty often coincides with arrival uncertainty. Researchers are urged to pay special attention to allocate resources in the best way possible. Erdem et al. (2012) develop a genetic algorithm to reschedule elective patients since the arrival of emergency patients may lead to the delay of elective surgeries and the disruptions of patient flow if without adequate resources. They provide hospitals with a reliable tool for making correct and timely decisions in admitting emergency patients by proposing a novel chromosome structure to solve the MILP model. Ferrand et al. (2010) compare the effect between focused and flexible resource uncertainty on patient waiting time and hospital-staff overtime to handle the flow of planned elective operations and unforeseen emergency operations.

5.1.4 Care requirement uncertainty

Except for duration, arrival and resource uncertainty, other types of uncertainty are also studied, such as care requirement uncertainty. Punnakitikashem et al. (2008) study the problem of assigning patients to nurses with the objective of minimizing excess workload for nurses, considering the fluctuations and uncertainty of patient. To solve the problem, they develop an IP model and adopt L-shaped method based on Benders decomposition. Holte and Mannino (2013) solve the medical resource allocation problem that takes into account uncertain patients requirements for medical care, such as the numbers and types of surgeries that will need to be scheduled. A general model is presented to generate MSS by a row and column generation algorithm.

5.2 Objective functions

Essentially, all the objectives are aimed at maximizing efficient usage of the operating theatre and minimizing the cost of resources. Researchers commonly solve the problem of determining the sequence for the relevant patients, with the objective of minimizing the sum of the expected waiting costs and the expected idling cost of the resources, including the operating rooms and the team of doctors (Guda et al. 2016). Table 9 provides an overview of the main objective functions of the reviewed papers.

5.3 Certain requirements

In some papers, the certain requirements in the surgery process are taken into account, for example, cleaning and disinfecting should be performed between two surgical procedures in the same room. There is an obligatory cleaning of the OR additionally after the surgical case of an infected patient such as MRSA infection (Cardoen et al. 2009b). This process results in a setup time between them. Marques et al. (2012c) set the cleaning and disinfecting time to 30 min between two surgeries operated in the same room. Doulabi et al. (2016a) present an effective algorithm for OR planning problem, allowing the cleaning time when switching from infectious to noninfectious cases. In their model, the starting time of an operation is later than the ending time of the previous surgery adds any cleaning time. Cardoen et al. (2009b) state that the cleaning is not needed when the next patient has the same infection exactly as the previous one. Besides, Cardoen et al. (2009b) also point out that when the last patient to be treated in an OR is infected, no additional cleaning is required to be performed in that the OR is thoroughly cleaned before close time. Moreover, Riise et al. (2016) point out that when an infected patient is situated at a surgery block that is followed by a block of a different surgeon without infection, there is again an obligatory cleaning and it must be entirely performed within the block of the infected patients surgery.

Besides the certain requirements originated from the surgery rules, there are also some special demands from the patients. Sometimes, they should be treated with special requirements and attention. For example, some patients, such as diabetics, elderly, and children, must be performed on at the beginning of the day. Similarly, some certain surgical specialties should be given higher priority. Researchers classify surgical specialties in different ways. Marques and Captivo (2015) divide surgery specialties into digestive and general surgery, thorax surgery, angiology and vascular surgery, otorhinolaryngology and urology. When it turns to specific specialty, cardiac surgeries and neurological surgeries have to be performed on a specific room (Silva et al. 2015). Furthermore, the urgency of patients is also an important factor. It depends on the presence of fast disease progression and the grade of pain or dysfunction and disability. An emergent surgery can be treated as a surgery with the highest priority

Table 9 Objective functions in the literature

Maximize the number of surgical cases to be scheduled	Lei et al. (2016), Guda et al. (2016), Castro and Marques (2015), Marques et al. (2015), Vancroonenburg et al. (2015), M'Hallah and Al-Roomi (2014), Vijayakumar et al. (2013) and Ogulata et al. (2008)
Maximize the use of ORs time	Doulabi et al. (2016a) and Saadouli et al. (2015)
Minimize the cost of ORs	Aringhieri et al. (2015a), Jebali and Diabat (2015), Agnetis et al. (2014), Martinelly et al. (2014), Zhang et al. (2014), Choi and Wilhelm (2014a, b), Abdelrasol et al. (2013), Vijayakumar et al. (2013), Meskens et al. (2013), Herring and Herrmann (2012), Tànfani and Testi (2010), Fei et al. (2008, 2009, 2010), Denton et al. (2010), Lamiri et al. (2008b) and Roland et al. (2007)
Minimize patient-related costs	Jebali and Diabat (2015), Fügener et al. (2014), Erdogan and Denton (2013), Lamiri et al. (2008b, c)
Minimize the costs of patients waiting time	Addis et al. (2016) and Erdogan and Denton (2013)
Minimize the number of ORs and required beds	Li et al. (2016), Essen et al. (2014) and Marcon et al. (2003)
Minimize the maximum makespan	Guido and Conforti (2017), Latorre-Núñez et al. (2016), Lei et al. (2016), Bastian et al. (2015), Saadouli et al. (2015), Baesler et al. (2015), Vancroonenburg et al. (2015), M'Hallah and Al-Roomi (2014), Meskens et al. (2013), Dekhici and Khaled (2010), Liu et al. (2011), Augusto et al. (2010), Perdomo et al. (2008), Arnaout and Kulbashian (2008) and Lamiri et al. (2008a)
Minimize the overtime	Hans et al. (2008); Al Hasan et al. (2018), Kroer et al. (2018) and Rizk and Arnaout (2012)
Minimize the number of used blocks	Landa et al. (2016) and Souki et al. (2009)
Maximize the satisfaction	Astaraky and Patrick (2015), Agnetis et al. (2014), Guinet and Chaabane (2003) and Ozkarahan (2000)
Minimize the transitions of surgeons between different ORs	Li et al. (2015) and Vijayakumar et al. (2013)

Table 10 Multi-stage scheduling problems in the literature

Two-stage	Rath et al. (2017), Berg and Denton (2017), Kim and Mehrotra (2015), Wang et al. (2015), Zhong et al. (2014), Qu et al. (2013), Dekhici and Khaled (2010), Rizk and Arnaout (2012), Zhu (2011), Batun et al. (2011), Fei et al. (2010), Punnakitikashem et al. (2008), Wachtel and Dexter (2008), Denton et al. (2007), Schedule (2006) and Hsu et al. (2003)
Three-stage	Xiang et al. (2015b), Ma and Demeulemeester (2013), Day et al. (2012), Editor and Hillier (2011), Ogulata et al. (2008), Testi et al. (2007) and Ogulata and Erol (2003)

because it is generally admitted directly to an OR (Min and Yih 2010a). Castro and Marques (2015) take three surgery priority levels into account. Priority one contains deferred urgency surgeries that must be operated in the first planning day. Priority two must be completed during the planning horizon, while the remaining surgeries can be performed in a later period.

In addition, some related resource requirements are also considered in some papers, including the materials, surgeons, and nurses. Materials refer to the types of the ORs, availability of rooms, equipment and medical material (Vissers and Beech 2005; Vancroonenburg et al. 2015; Martinelly et al. 2014). Surgeon preference and material are taken into account in (Meskens et al. 2013). Nurse's preference is also taken into account by researchers. Pardalos et al. (2013) use the binary IP model to formulate and solve the nurse scheduling problem that satisfies the nurse's preference (NSP) maximally.

5.4 Multiple stages

Considering the scope of the studied problem, some researchers divide the processes of OR planning and scheduling into several stages, as shown in Table 10. Usually, the first stage allocates the resources through multiple surgeries, and prescribes the sequence of surgeries according to the resources. Thus, a scheduled start time for surgeries can be provided under the assumption that each surgery should be scheduled as early as possible. The second stage determines the actual starting time of surgical cases and assigns overtime resources according to the implementation time of the previous surgeries, so as to make sure that all operations are completed using the sequence determined in the first stage (Batun et al. 2011). Most papers follow the above two-stage process. Zhang et al. (2014) suggest a multi-stage stochastic programming model using a two-stage stochastic programming approximation strategy. Kim and Mehrotra (2015) propose a two-stage stochastic integer program with mixed-integer recourse. Denton et al. (2010) describe a model which is a two-stage stochastic linear program with binary decisions in the first stage and simple recourse in the second stage. Still, some researchers divide the processes into three stages. Testi et al. (2007) propose a three-phase approach for operating theatre schedules. In the first phase, the available OR time is allocated among the wards. In the second phase, a MSS is developed and in the third phase, the elective cases are scheduled in each allocated block.

Table 11 Mathematical models in the literature

Bin-packing model	Li et al. (2016), Vancroonenburg et al. (2015), Dios et al. (2015), Molina-Pariente et al. (2015b), Agnetis et al. (2014), Vijayakumar et al. (2013), Erdogan et al. (2011), Vlah et al. (2011), Batun et al. (2011), Denton et al. (2010), Fei et al. (2010), Tànfani and Testi (2010), Hans et al. (2008) and Marcon and Dexter (2006)
Flow-shop model	Wang et al. (2015), Souki (2011), Fei et al. (2010), Pham and Klinkert (2008), Chern et al. (2008), Lamiri et al. (2008a), Schedule (2006), Jebali et al. (2006) and Guinet and Chaabane (2003)
Stochastic model	Kim et al. (2018), Guda et al. (2016), Saadouli et al. (2015), Bruni et al. (2015), Jebali and Diabat (2015), Kim and Mehrotra (2015), Tsai and Teng (2014), Wang et al. (2014), Erdogan and Denton (2013), Mancilla and Storer (2012), Riise and Burke (2011), Batun et al. (2011), Min and Yih (2010b), Fei et al. (2009, 2010), Hans et al. (2008), Lamiri et al. (2008a, b), Denton et al. (2007) and Marcon and Dexter (2006)
Multi-criteria model	Marques et al. (2014, 2015), Marques and Captivo (2015), Batun et al. (2011), Gul et al. (2011), Testi et al. (2007), Dexter et al. (2005), Guinet and Chaabane (2003) and Ogulata and Erol (2003)

6 Mathematical models

Surgery planning and scheduling problems have been formalized in many different models including bin-packing model, flow-shop model, stochastic model and multi-criteria model, etc. In Table 11, we list the mathematical models proposed in the papers reviewed in this section.

6.1 Bin-packing model

Bin-packing model has been widely used to find the mix of surgical cases allocated to multi-ORs (Dexter et al. 1999). Many researchers apply the bin-packing models for OR planning optimization, and their outcomes are of high importance to the practitioners. Under this circumstance, the ORs represent the bins and the surgeries represent the items to be packed in the bins. The ORs are available for a fixed time during the day. Two types of bin-packing models have been studied: on-line and off-line. In the on-line bin-packing model, urgent operations are scheduled sequentially one at a time, while in the off-line version, operations are batched and simultaneously assigned to ORs (Erdogan et al. 2011). Marcon and Dexter (2006) apply first fit on-line bin packing rule for selecting the cases to be moved. Vijayakumar et al. (2013)conceptualize the surgery scheduling problem as an unequal-sized, multi-bin and multi-dimensional dual bin-packing problem which is the dual of bins required to assign a given set of items. Testi et al. (2007) solve a bin packing-like problem to select the sessions for each surgery group, but the bin packing-like model and its solution are currently applicable to small problems only. Fei et al. (2010) regard the planning phase problem as a resource-constrained bin packing problem after setting their hypotheses. Hans et al. (2008) study the problem of assigning surgeries and sufficient planned relaxation time to surgical days with the objective of minimizing the total planned slack. They point out that the intervention assignment problem is a generalization of general bin packing problem with unequal bins. Smart algorithms are used and portfolio effect is exploited to free much OR-capacity.

6.2 Flow-shop model

Since operations may go through several processes, it can be modeled as flow-shop problem under such circumstance. Flow-shop model problem is known to be NP-hard and has been addressed by several papers (Pham and Klinkert 2008; Jebali et al. 2006; Fei et al. 2010; Guinet and Chaabane 2003; Souki 2011). Guinet and Chaabane (2003) and Wang et al. (2015) model the daily scheduling problem as a two-stage no-wait hybrid flow-shop problem. Wang et al. (2015) study a daily schedule problem related to the patient flow including ORs and post-anesthesia care unit. Combined with heuristic rules, a discrete particle swarm optimization algorithm is employed to give the optimal number of daily open ORs and recovery beds. The daily scheduling problem depending on the results obtained in the planning phase, is regarded as a two-stage flow-shop problem in Souki (2011) and has been addressed in Fei et al. (2010), Jebali et al. (2006), Guinet and Chaabane (2003) and Vancroonenburg et al. (2015).

6.3 Stochastic model

OR planning and scheduling problem is commonly solved in deterministic way for simplicity where the duration of the operations is assumed to be deterministic without fluctuation. However, in real situations, even the same type of surgery operated by the same surgeon may be of different durations, that is, it should be stochastic. Recently, more and more researchers solve OR planning problems by stochastic mathematical programming model (Kim and Mehrotra 2015; Guda et al. 2016; Min and Yih 2010a; Lamiri et al. 2008b). Guda et al. (2016) study a surgical scheduling problem as a single-machine earliness/tardiness problem(SET) in stochastic scheduling theory, with the order of processing and the due-dates as decisions. Min and Yih (2010a) propose a two-stage stochastic programming model for elective surgery case scheduling problem and solve the model using the sample average approximation. Erdogan and Denton (2013) formulate the model as a two-stage stochastic linear program. In the first model, patients may not show up at the expected arrival time while in the second model, patients are scheduled dynamically one by one after they apply appointments.

6.4 Multi-criteria model

The multi-criteria model commonly considers multiple objective functions. Only a few papers consider explicitly a multi-criteria approach. Gul et al. (2011) develop a discrete event simulation model to compare several heuristics for scheduling an Outpatient Procedure Center. Also, they use a bi-criteria Genetic Algorithm to get better solutions for the daily scheduling problem and investigate the efficiency of the algorithm under the circumstance in which surgeries are allowed to be moved to other days. Marques et al. (2015) settle a bi-criteria problem composed of assigning an intervention date, a starting time and an OR for elective surgeries by developing a constructive and improving heuristic to search for efficient solutions. The bi-criteria approach performs well to build surgical plans. In another article, Marques and Captivo (2015) provide a bi-criteria evolutionary algorithm for an elective surgery scheduling problem of a public hospital. It is an evolutionary algorithm to approximate the set of non-dominated solutions of this bi-criteria optimization problem. Testi et al. (2007) propose optimization models for the weekly scheduling of ORs. They distribute OR time among the wards according to different criteria, such as financial criteria, historical utilization and waiting list. Gul et al. (2011) compare twelve different heuristics of sequencing and patient appointment time setting, regarding two competing criteria of OR overtime and patient waiting time. They also prove that the bi-criteria genetic algorithm is effective in allowing surgery to be changed to other days.

7 Solutions and methods

A variety of effective solutions and methods has been developed for solving surgery planning and scheduling problems. Solution approaches for the optimization problem vary from exact approaches to meta-heuristics. These choices are determined by the size and complexity of the problem. We divide the solutions and methods into exact algorithms, heuristics, simulations and Markov decision process as Table 12 shows.

7.1 Exact algorithms

Exact algorithm refers to an algorithm that always finds the optimal solution to an optimization problem, as opposed to heuristics that may sometimes produce worse solutions and a subset of these are the approximation algorithms. Exact algorithms are usually used for small-scale instances. Table 13 lists the various exact solutions or evaluation techniques that are applied to our problem settings. We classify exact algorithms as column generation, dynamic programming, branch and cut, branch and bound and branch-and-price.

7.1.1 Column generation

Many researchers use the column generation algorithm to solve the problem, especially in combinatorial optimization problem. Fei et al. (2006) solve a weekly operating room planning problem of allocating patients to blocks using a column-generation-based heuristic and address the following daily operating room scheduling problem of determining the sequence of the patients with a hybrid genetic algorithm. In another paper, Fei et al. (2010) also discuss these two problems but consider the availability of recovery beds at the same time. The planning problem is described as a set-partitioning integer-programming model and also solved by a column-generation-based heuristic

Table 12 Solutions and methods in the literature

Exact algorithms	See Table 13
Heuristic algorithms	See Table 14
Simulations	
Monte Carlo simulation	Huang et al. (2018), Landa et al. (2016), Truong (2015), Lee and Yih (2014), Pulido et al. (2014), Lamiri et al. (2009), Hans et al. (2008), Denton et al. (2007) and Lamiri et al. (2007)
Discrete-event simulation (DES)	Koppka et al. (2018), Bam et al. (2017), Xiang et al. (2015a), Saadouli et al. (2015), Van Der Kooij et al. (2015), Baesler et al. (2015), Brown et al. (2014), Peng et al. (2014), Ma and Demeulemeester (2013), Niu et al. (2013), Lehtonen et al. (2013), Saremi et al. (2013), Gul et al. (2011) and Marcon and Dexter (2006)
Others	Díaz-lópez et al. (2018), Kim et al. (2018), Rachuba and Werners (2017), Bai et al. (2017), Molina-Pariente et al. (2015a), Astaraky and Patrick (2015), Zhang and Xie (2015), Marques and Captivo (2015), Hosseini and Taaffe (2015), Wang et al. (2015), Liang et al. (2015), Arcidiacono et al. (2015), M'Hallah and Al-Roomi (2014), Matta et al. (2014), Agnetis et al. (2014), Cai et al. (2014), Zhong et al. (2014), Abdeljaouad et al. (2014), Zhang et al. (2014), Chan and Green (2013), Paul and MacDonald (2013), Chandoul et al. (2012), Day et al. (2012), Marques et al. (2012a, b), Shylo and Prokopyev (2012), Schütz and Kolisch (2012), Hall (2012), Agnetis et al. (2012), Su et al. (2011), Price et al. (2011), Joustra et al. (2011), Min and Yih (2010b), Kapamara and Petrovic (2009), Zhang et al. (2009), Arnaout and Kulbashian (2008), Testi et al. (2007), Vissers and Beech (2005), Ogulata and Erol (2003), Hsu et al. (2003), Marcon et al. (2003), Dexter et al. (1999) and Weiss (1990)
Markov decision processes (MDPs)	Astaraky and Patrick (2015), Barz and Rajaram (2015), Schütz and Kolisch (2012)

Table 13 Exact algorithms in the literature

Column generation	Day et al. (2012), Fei et al. (2006, 2010), Cardoen et al. (2009b), Beliën and Demeulemeester (2008), Oostrum et al. (2008) and Lamiri et al. (2008a)
Dynamic programming	Rath et al. (2017), Truong (2015), Astaraky and Patrick (2015), Bastian et al. (2015), Wang et al. (2014), Zhang et al. (2014), Herring and Herrmann (2012), Liu et al. (2011), Augusto et al. (2010), Cardoen et al. (2009b), Beliën and Demeulemeester (2008) and Fei et al. (2008)
Branch and bound	Li et al. (2016), Bastian et al. (2015), Cardoen et al. (2009a), Fügener et al. (2014), Oostrum et al. (2008) and Cardoen et al. (2009a)
Branch and cut	Kim and Mehrotra (2015), Cardoen et al. (2009a), Erdogan and Denton (2013), Chan and Green (2013) and Batun et al. (2011)
Branch and price	Doulabi et al. (2016a), Ma et al. (2011), Cardoen et al. (2009b), Fei et al. (2008), Beliën and Demeulemeester (2008), Purnomo and Bard (2007) and Barnhart et al. (1998)

procedure. Beliën and Demeulemeester (2008) study both the nurse and the operating room scheduling process using column generation approach. They find the legal column with the most negative reduced cost and finally establish surgery and nurse schedules with considerable savings achieved.

7.1.2 Dynamic programming

The dynamic programming algorithm is an implicit enumeration technique implied as a discrete optimization method for sequential decision-making. For a given problem, dynamic programming algorithms solve different parts of the problem (i.e., sub-problems), where each sub-problem involves a subset of the decisions. Augusto et al. (2010) study the effect of allowing patients to recover in OR when recovery bed is unavailable. They use dynamic programming to solve several sub-problems separately in order to obtain the optimal start times for each patient. Generally, dynamic programming optimization algorithm is used to address the pricing problem to produce a column with the most negative reduced cost and validate its high computational efficiency especially when compared with a mixed integer linear programming methodology. Wang et al. (2014) apply a dynamic programming algorithm to address an operating room allocation problem. They develop a stochastic model to minimize the overall surgical cost when surgery durations and emergency demands are taken into account. Cardoen et al. (2009b) state a surgical case sequencing problem in which the sequence of patients in the OR of an independent outpatient unit has to be determined. They use a dynamic programming approach and a mixed integer linear programming approach to solve the NP-hard problem.

7.1.3 Branch-and-bound

Another effective way to find the optimality solution is branch-and-bound. Li et al. (2016) utilize a lower bound with a guaranteed performance. The branch-and-bound algorithm deals with the spread constraints that a surgeon may wish to have all his cases scheduled either in the morning or the afternoon. Cardoen et al. (2009a) formulate a multiple objective optimization model for the daily scheduling of ORs. They point out that implicit enumeration through branch-and-bound is beneficial to solve the surgical case scheduling problem. Based on integer programming and branch-and-bound, they introduce exact algorithms and heuristic algorithms. They select a depth-first approach and make the combinations of the branching schemes. Li et al. (2016) study the problem of rescheduling surgery start times to reduce OR costs of staffing. Based on a lower bound construction algorithm, they use the lower bound in a branch-and-bound algorithm to solve the rescheduling problem and study how rescheduling affects surgeons delays and overtime.

7.1.4 Branch-and-cut

Branch-and-cut is a method of combinatorial optimization to solve integer linear programs, and it involves running a branch-and-bound algorithm and using cutting planes to tighten the linear programming relaxations. An integer L-shaped algorithm is widely used in an branch-and-cut framework (Kim and Mehrotra 2015; Chan and Green 2013; Batun et al. 2011). Batun et al. (2011) state a two-stage stochastic mixed integer programming model aimed at minimizing overall costs during operations and in this way, measure the benefits of pooling the ORs as a shared resource. They employ a L-shaped algorithm within a branch-and-cut framework to solve the main problem by adding the optimality cuts during branch and bound. Kim and Mehrotra (2015) study the problem of determining staffing schedules considering uncertain demand, and adjust the schedules a few days before the actual date. They present two methods to enhance the standard integer L-shaped, in the form of a multi-cut aggregation approach and in the form of pre-identifying thin branching directions. Based on auxiliary branching variables, they find new directions for branch-and-cut processes. The CPU time is demonstrated to be greatly improved during the branch-and-cut stage.

7.1.5 Branch-and-price

The philosophy of branch-and-price is similar to that of branch-and-cut except that the procedure puts emphasis on column generation instead of row generation (Fei et al. 2008; Doulabi et al. 2016b; Cardoen et al. 2009b). Fei et al. (2008) study a problem of assigning surgical cases aimed at minimizing total operating cost. They design a branch-and-price algorithm which combines branch-and-bound method with column generation method to solve it. In the probem, each node is a linear relaxation problem of a set partitioning problem and is solved by a column generation method. In the same way, Cardoen et al. (2009b) solve a problem of sequencing daily surgical cases by a dynamic programming approach and embed the column generation loop in an enumerative branch-and-price framework to obtain integer variables. They propose several branching schemes and branching strategies and compare the influence on the quality of solutions. Beliën and Demeulemeester (2008) develop an integrated model for nurses and ORs scheduling problem. Column generation approach is used to cope with it. They propose a constraint branching scheme and introduce some techniques to improve the performance of the branch-and-price algorithm. Perdomo et al. (2008) propose a new integer programming model for cyclic and preference scheduling of nurses and employ a branch-and-price algorithm to find optimal solutions. The algorithm takes advantage of several branch rules and an efficient rounding heuristic algorithm.

7.2 Heuristics

Table 14 lists the various heuristics that are used to find optimal solutions for different problem settings in the literature. We divide these heuristics into six categories: heuristics based on exact methods, constructive heuristics, improvement heuristics, metaheuristics, linear programming (LP) based heuristics and dispatching-rule based heuristics.

Heuristics based on exact methods include heuristic branching strategy (Li et al. 2016; Kim and Mehrotra 2015; Astaraky and Patrick 2015; Fügener et al. 2014; Car-

Table 14 Literature on heuristics

	Heuristics based on exact methods				Constructive	Improvement	Metaheuristics						Dispatching-rule based heuristics								
	Branching	CG	DP	Others			GA	SA	TS	VNS	ACO	Others	LP	FFD	Relax and fix	Lagrangian relaxation	FCFS	LPT	SPT	FIFO	Others
Guido and Conforti (2017)			√				√														
Roshanaei et al. (2017b)														√							
Ceschia and Schaerf (2016)			√					√													
Lei et al. (2016)													√								
Li et al. (2016)	√				√								√								
Riise et al. (2016)												√									
Doulabi et al. (2016a)			√		√																
Baesler et al. (2015)								√										√	√	√	
Vancroonenburg et al. (2015)										√											
Kim and Mehrotra (2015)	√	√																			
Marques et al. (2015)					√	√															
Marques and Captivo (2015)					√																
Molina-Pariente et al. (2015b)			√		√					√											
Silva et al. (2015)													√		√						
Aringhieri et al. (2015a)												√									

Table 14 continued

	Heuristics based on exact methods				Constructive	Improvement	Metaheuristics						Dispatching-rule based heuristics								
	Branching	CG	DP	Others			GA	SA	TS	VNS	ACO	Others	LP	FFD	Relax and fix	Lagrangian relaxation	FCFS	LPT	SPT	FIFO	Others
Truong (2015)			√																		
Astaraky and Patrick (2015)	√		√										√								
Dios et al. (2015)			√																		
Xiang et al. (2015a)			√								√						√				√
Schmid and Doerner (2014)												√									
Abdeljaouad et al. (2014)												√						√			
Fügener et al. (2014)	√			√		√															
Pulido et al. (2014)																					√
Wang et al. (2014)		√	√																		
Zhang et al. (2014)			√																		√
Cardoen et al. (2009a)	√	√											√								√
Vijayakumar et al. (2013)														√							
Saremi et al. (2013)			√						√												
Niu et al. (2013)						√			√												
Erdogan and Denton (2013)	√		√										√								

Table 14 continued

	Heuristics based on exact methods				Constructive	Improvement	Metaheuristics							Dispatching-rule based heuristics							
	Branching	CG	DP	Others			GA	SA	TS	VNS	ACO	Others	LP	FFD	Relax and fix	Lagrangian relaxation	FCFS	LPT	SPT	FIFO	Others
Herring and Herrmann (2012)			√																		√
Marques et al. (2012c)							√														
Marques et al. (2012b)						√															
Mancilla and Storer (2012)									√												
Carter et al. (2012)			√			√															
Marques et al. (2012a)					√																
Batun et al. (2011)	√																				
Liu et al. (2011)			√		√																
Vlah et al. (2011)						√				√		√									
Ma et al. (2011)	√	√											√								
Denton et al. (2010)																		√			
Roland et al. (2010)							√														
Fei et al. (2010)			√	√	√		√														
Augusto et al. (2010)			√													√					
Fei et al. (2009)			√	√						√											
Lamiri et al. (2009)					√	√															
Beliën et al. (2009)								√													
Cardoen et al. (2009b)		√	√			√	√						√								
Cardoen et al. (2009a)	√																				

Table 14 continued

	Heuristics based on exact methods				Constructive	Improvement	Metaheuristics							Dispatching-rule based heuristics							
	Branching	CG	DP	Others			GA	SA	TS	VNS	ACO	Others	LP	FFD	Relax and fix	Lagrangian relaxation	FCFS	LPT	SPT	FIFO	Others
Lamiri et al. (2008a)		√	√																		
Perdomo et al. (2008)			√													√					
Fei et al. (2008)			√	√																	
Oostrum et al. (2008)	√	√											√								
Hans et al. (2008)					√	√															
Lamiri et al. (2008c)				√		√															
Beliën and Demeulemeester (2008)		√	√	√									√								
Lamiri et al. (2007)				√		√															
Denton et al. (2007)				√											√						√
Fei et al. (2006)			√	√			√														
Marcon and Dexter (2006)			√															√	√		
Guinet and Chaabane (2003)				√	√																
Hsu et al. (2003)									√												
Barnhart et al. (1998)	√	√											√								
Dexter et al. (1999)					√																
Ozkarahan (1995)																		√			

doen et al. 2009a; Erdogan and Denton 2013; Batun et al. 2011; Ma et al. 2011; Oostrum et al. 2008; Cardoen et al. 2009a; Barnhart et al. 1998), column generation(CG) based heuristic (Kim and Mehrotra 2015; Wang et al. 2014; Cardoen et al. 2009a; Barnhart et al. 1998; Ma et al. 2011; Cardoen et al. 2009b; Lamiri et al. 2008a; Oostrum et al. 2008; Beliën and Demeulemeester 2008), dynamic programming (DP) (Guido and Conforti 2017; Ceschia and Schaerf 2016; Doulabi et al. 2016a; Molina-Pariente et al. 2015b; Truong 2015; Astaraky and Patrick 2015; Dios et al. 2015; Xiang et al. 2015a; Wang et al. 2014; Zhang et al. 2014; Saremi et al. 2013; Erdogan and Denton 2013; Herring and Herrmann 2012; Carter et al. 2012; Liu et al. 2011; Fei et al. 2006, 2008, 2009, 2010; Augusto et al. 2010; Cardoen et al. 2009b; Lamiri et al. 2008a; Perdomo et al. 2008; Beliën and Demeulemeester 2008; Marcon and Dexter 2006) and others (Fügener et al. 2014; Fei et al. 2008, 2009, 2010; Lamiri et al. 2008c; Beliën and Demeulemeester 2008; Lamiri et al. 2007; Denton et al. 2007; Fei et al. 2006; Guinet and Chaabane 2003). Cardoen et al. (2009b) report on the application of mixed integer programming (MIP) to optimize operational daily schedules. They employ iterated mixed integer linear programming (MILP) procedures plus a heuristic branch-and-bound (B&B) procedure and compare with the results in Cardoen et al. (2009a). Fei et al. (2010) describe a planning problem to decide the date of surgery for each patient that minimizes the overtime cost in ORs and report on a daily scheduling problem to decide sequence of surgeries that minimizes the idle time between surgeries. They solve the planning problem by a column-generation-based heuristic (CGBH) algorithm and cope with the scheduling problem by a hybrid genetic algorithm, using a tabu search procedure as the local improved operator. They validate the performance of the column-generation-based heuristic (CGBH) algorithm through a comparison between the schedules generated by their method and the actual schedules. In another article, Fei et al. (2009) use an open scheduling strategy in the mathematical model to assign surgeries during 1 week. They apply a dynamic programming procedure to assist an explicit column generation procedure to find the optimal solution of the linear master problem.

In Table 14, we also present the constructive heuristics existing in the literature for solving OR scheduling problem (Li et al. 2016; Doulabi et al. 2016a; Marques et al. 2012a, 2015; Marques and Captivo 2015; Molina-Pariente et al. 2015b; Liu et al. 2011; Fei et al. 2010; Lamiri et al. 2009; Hans et al. 2008; Guinet and Chaabane 2003; Dexter et al. 1999). Hans et al. (2008) provide numerous constructive heuristics and local search methods that use the statistical data of the surgery durations to take advantage of the portfolio effect and thus to minimize the slack. It proves that their method releases a large amount of OR capacity and therefore additional operations can be performed.

Furthermore, we summarize the improvement heuristics in the literature for solving OR scheduling problem (Marques et al. 2012b, 2015; Fügener et al. 2014; Niu et al. 2013; Carter et al. 2012; Vlah et al. 2011; Lamiri et al. 2009; Cardoen et al. 2009b; Hans et al. 2008; Lamiri et al. 2008c, 2007). For example, Lamiri et al. (2009) propose four improvement heuristics, which are sequential improvement heuristic, local optimization heuristic, pair-wise switching heuristic and multi-start heuristic. They compare the performance of these methods for elective surgery planning in numerical experimentations.

Meta-heuristics is widely chosen for the optimization problem. In combinatorial optimization, by searching over a large set of feasible solutions, metaheuristics can often find good solutions with less computational effort than optimization algorithms, iterative methods, or simple heuristics. We incorporate genetic algorithm (GA) heuristic (Guido and Conforti 2017; Marques et al. 2012c, 2014; Roland et al. 2010; Fei et al. 2010; Cardoen et al. 2009b; Fei et al. 2006), simulated annealing (SA) heuristic (Ceschia and Schaerf 2016; Baesler et al. 2015; Ceschia and Schaerf 2011; Beliën et al. 2009), tabu search (TS) based heuristic (Niu et al. 2013; Saremi et al. 2013; Mancilla and Storer 2012; Hsu et al. 2003), variable neighborhood search (VNS) (Molina-Pariente et al. 2015b; Vancroonenburg et al. 2015; Vlah et al. 2011; Fei et al. 2009), ant colony optimization (ACO) heuristic (Xiang et al. 2015a) and others (Riise et al. 2016; Aringhieri et al. 2015b; Schmid and Doerner 2014; Abdeljaouad et al. 2014; Vlah et al. 2011) into meta-heuristics. Guido and Conforti (2017) apply a novel genetic algorithm to manage ORs and plan surgeons, and allow to update waiting lists status and staffing availability for the following cycle. They construct an initial population with suitable and semi-feasible sets of chromosomes, which is the seed for the evolving computational process. Ceschia and Schaerf (2016) extend their study to consider constraints on the utilization of ORs for patients in the patient admission scheduling problem. A simulated annealing metaheuristic is proposed based on local search to search for optimal solutions. Saremi et al. (2013) present three simulation-based optimization methods to cope with surgery appointment with the objective of minimizing the patients waiting time, which are simulation-based tabu search, integer programming enhanced tabu search and binary programming enhanced tabu search. They consider the limited availability of various kinds of resources and the compatibility of surgeon and patient categories. Vlah et al. (2011) develop a heuristic algorithm based on variable neighborhood search to solve the management problem under the restrictions of hospitals medical condition and medical machines. They prove that the heuristic algorithm performs better than both commercial software and calculating by hand. Xiang et al. (2015a) study a surgery scheduling problem with arrival uncertainty, in which they allocate the resources to the scheduled surgeries so that the balance of resource utilization can be ensured. They propose an ant colony optimization algorithm based on the similarities of flexible job shop scheduling problem. The features of positive feedback and self-organizing in ant colony optimization algorithm are proved to perform well in the uncertainty.

Dispatching-rule based heuristics include first fit decreasing (FFD)-based heuristic (Roshanaei et al. 2017b; Vijayakumar et al. 2013), relax-and-fix heuristic (Silva et al. 2015; Denton et al. 2007), lagrangian relaxation heuristic (Augusto et al. 2010; Perdomo et al. 2008), heuristic of first-come-first-served (FCFS) (Xiang et al. 2015a), longest processing time (LPT) heuristic (Baesler et al. 2015; Abdeljaouad et al. 2014; Denton et al. 2010; Marcon and Dexter 2006; Ozkarahan 1995), shortest processing time (SPT) heuristic (Baesler et al. 2015; Marcon and Dexter 2006), first-in-first-out (FIFO) heuristic (Baesler et al. 2015) and others (Xiang et al. 2015a; Pulido et al. 2014; Zhang et al. 2014; Cardoen et al. 2009a; Herring and Herrmann 2012; Denton et al. 2007). Vijayakumar et al. (2013) propose an efficient first fit decreasing-based heuristic. In FFD heuristic, they first sort cases based on the priorities, and then use several rules based on the expected surgery times to break the ties. Finally, they assign the sorted cases one-by-one according to an assignment rule to derive a complete schedule. Roshanaei et al. (2017b) solve the packing sub-problems via the first fit decreasing-based heuristic to find a feasible solution with the advantage that they can detect optimal sub-problems without solving them. Silva et al. (2015) discuss the problem of assigning surgeries in accordance with staffings skills to maximize the ORs utilization. They employ linear programming-based heuristic to construct a candidate surgery assignments and use the relax-and-fix heuristic to solve the optimality gap in the computational experiments. Augusto et al. (2010) study the OR scheduling problem in which patients are allowed to recovery in the OR when recovery beds are unavailable, taking into account transporters, ORs and recovery beds. They propose a Lagrangian relaxation-based method and validate the efficiency of the method through numerical experiments. Baesler et al. (2015) present a discrete-event simulation model to study the OR scheduling problem in which pre-operative and post-operative, setup and recovery are taken into account. They implement three dispatching rules, shortest processing time, longest processing time and first-in-first-out combined with a SA algorithm to search for better patient schedules.

7.3 Simulations

Simulation tests are conducted to further evaluate the performance of proposed models for a wider range of cases. Simulation models are more flexible in terms of assumptions about the probability distributions of surgery durations, although they do not provide closed form solutions like the queuing models. Many studies consider the simulation in the problem of planning and scheduling of OR, especially in the stochastic problem. The input of the simulation depends on the assumptions of the problems, for example, whether the duration of the surgical cases or the arrival time of the patients are stochastic. Ogulata and Erol (2003) point out that distribution of operation time types has an important influence on the optimum capacity utilization via the analysis of variance conducted on the simulation. Astaraky and Patrick (2015)study the problem of scheduling patients in a multiple level system. They apply a simulation-based approach to Policy Iteration method to identify when it is necessary to use overtime of ORs as well as take advantage of downstream resources.

As is shown in Table 12, we divide simulations into Monte Carlo simulation, Discrete-event simulation (DES) and others. Monte Carlo simulation is wildly used for scenario reduction (Pulido et al. 2014; Lamiri et al. 2008b). Lamiri et al. (2008b) propose a Monte Carlo optimization method which combines both Monte Carlo simulation and mixed integer programming (MIP). They use Monte Carlo simulation algorithm to estimate the exact cost of each resulting optimal solution. Discrete-event simulation (DES) is also commonly used in the experiments. M'Hallah and Al-Roomi (2014) propose a discrete event simulation method for the problem of off-line and on-line planning and scheduling of surgeries with the goal of ORs utilization enhancement. They compare the output of the simulation model with the actual situation and validate the efficiency. Hosseini and Taaffe (2015) calculate the number of ORs and describe a model to assign models to surgeons. They use a trace-driven simulation, which allow them to observe how well the blocks could accommodate the actual surgical demands.

7.4 Markov decision process (MDP)

Markov Decision Process (MDP) is useful to study a wide range of optimization problems which can be solved via dynamic programming and reinforcement learning. They are used in a wide area of disciplines, including health care, robotics, automatic control, economics, and manufacturing. MDPs is the most useful stochastic dynamic programming method for dealing with the allocation of patients to server and appointment day and time (Ahmadi-Javid et al. 2017). Astaraky and Patrick (2015) present a MDP model to schedule patients into a predestined master surgical scheduling. Schütz and Kolisch (2012) describe the OR scheduling problem as a continuous-time MDP and solve it through simulation-based approximate dynamic programming combined with a discrete event simulation (DES) of the service period. Barz and Rajaram (2015) study a problem of patient admission and scheduling that maximizes expected contribution net of overbooking costs. They describe the control process as a MDP and use dynamic programming to derive an upper bound bounds so as to get approximated marginal values for decision makers.

8 Conclusions

Operating room planning and scheduling is a complex and challenging task. We review the literature from the perspectives of decision level, scheduling strategy, patient classifications, problem features (e.g., uncertainty and objectives), mathematical models, solutions and methods. The studies reviewed in this paper clearly indicate that different decisions in different levels have a significant effect on the performance of the surgical center. It is a decision procedure over a relatively long period, including short-time planning, medium-time planning and long-time planning to satisfy different needs of hospital managers. We notice that most of the research is directed towards the scheduling problem within everyday horizon, which is very close to the actual situation. Although long-term schedule is convenient for surgeons and patients to plan their personal time in advance, there are sometimes minor changes in the waiting list of patients for dealing with emergencies. Nowadays, although a great deal of theoretical work has been published, none of them seems to have a profound effect on the real-word practice of OR management. With regard to the primary purpose of future research, there is still a lot to do to narrow the gap between theory and practice. We will conduct the survey along this line to make more efficient surgical research in OR scheduling in the future.

Uncertainty is inherent to surgical services and cannot be ignored. Next to the uncertainty in the case of emergencies, researchers should also put effort into the study of stochastic surgical durations and the influence on the surgical center practice. Meanwhile, based on the study of uncertainty, a better integration of the compatible resources should be favored. Until now, only half contributions take such integration into account. We recognize that this proposal expands the scope of the problem again, while also increasing the difficulty of obtaining reasonable results quickly. Thus, rigorous research is required to reveal the dynamics of a wider range of environmental factors on uncertainty of OR scheduling.

The analysis of the literature reveals that researchers are paying more attention to the problems of combined resources with an increased complexity. Accordingly, it may be useful to find new and more comprehensive performance indicators that a manager should consider. In addition, we can further explore the relationship between policy and case-mix, duration features and availability of ORs.

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References

Abdeljaouad MA, Saadani NEH, Bahroun Z (2014) A dichotomic algorithm for an operating room scheduling problem. In: 2014 international conference on control, decision and information technologies (CoDIT). IEEE, pp 134–139

Abdelrasol ZY, Harraz N, Eltawil A (2013) A proposed solution framework for the operating room scheduling problems. World Congr Eng Comput Sci 2:1149–1157. https://doi.org/10.1007/s10729-006-9005-4

Adan I, Bekkers J, Dellaert N, Vissers J, Yu X (2009) Patient mix optimisation and stochastic resource requirements: a case study in cardiothoracic surgery planning. Health Care Manag Sci 12(2):129–141. https://doi.org/10.1007/s10729-008-9080-9

Addis B, Carello G, Grosso A (2016) Operating room scheduling and rescheduling: a rolling horizon approach. Flex Serv Manuf J 28(1–2):206–232. https://doi.org/10.1007/s10696-015-9213-7

Addis B, Carello G, Tànfani E (2014) A robust optimization approach for the advanced scheduling problem with uncertain surgery duration in operating room planning–an extended analysis. Hot Working Tech 27(12):3631–3644

Agnetis A, Coppi A, Corsini M, Dellino G, Meloni C, Pranzo M (2012) Long term evaluation of operating theater planning policies. Oper Res Health Care 1(4):95–104. https://doi.org/10.1016/j.orhc.2012.10.001

Agnetis A, Coppi A, Corsini M, Dellino G, Meloni C, Pranzo M (2014) A decomposition approach for the combined master surgical schedule and surgical case assignment problems. Health Care Manag Sci 17(1):49–59. https://doi.org/10.1007/s10729-013-9244-0

Ahmadi-Javid A, Jalali Z, Klassen KJ (2017) Outpatient appointment systems in healthcare: a review of optimization studies. Eur J Oper Res 258(1):3–34. https://doi.org/10.1016/j.ejor.2016.06.064

Aij KH, Simons FE, Visse M, Widdershoven GAM (2014) A focus on throughput: lean improvement of nurse scheduling in the operating theatre. Glob J Manage Bus Res 47(1):81–87

Al Hasan H, Guéret C, Lemoine D, Rivreau D (2018) Dynamic surgical case scheduling with sterilizing activities constraints: a rolling horizon approach. In: Roadef 2018

Arcidiacono G, Wang J, Yang K (2015) Operating room adjusted utilization study. Int J Lean Six Sigma 6(2):111–137. https://doi.org/10.1108/IJLSS-02-2014-0005

Aringhieri R, Landa P, Soriano P, Tànfani E, Testi A (2015) A two level metaheuristic for the operating room scheduling and assignment problem. Comput Oper Res 54:21–34. https://doi.org/10.1016/j.cor.2014.08.014

Aringhieri R, Landa P, Tànfani E (2015) Assigning surgery cases to operating rooms: a VNS approach for leveling ward beds occupancies. Electron Notes Discrete Math 47:173–180. https://doi.org/10.1016/j.endm.2014.11.023

Arnaout JPM, Kulbashian S (2008) Maximizing the utilization of operating rooms with stochastic times using simulation. In: Proceedings of the 40th conference on winter simulation, pp 1617–1623

Astaraky D, Patrick J (2015) A simulation based approximate dynamic programming approach to multi-class, multi-resource surgical scheduling. Eur J Oper Res 245(1):309–319. https://doi.org/10.1016/j.ejor.2015.02.032

Augusto V, Xie X, Perdomo V (2010) Operating theatre scheduling with patient recovery in both operating rooms and recovery beds. Comput Ind Eng 58(2):231–238. https://doi.org/10.1016/j.cie.2009.04.019
Baesler F, Gatica J, Correa R (2015) Simulation optimisation for operating room scheduling. Int J Simul Model 14(2):215–226. https://doi.org/10.2507/IJSIMM14(2)3.287
Bai M, Storer RH, Tonkay GL (2017) A sample gradient-based algorithm for a multiple-OR and PACU surgery scheduling problem. IISE Trans 49(4):367–380. https://doi.org/10.1080/0740817X.2016.1237061
Bam M, Denton BT, Van Oyen MP, Cowen ME (2017) Surgery scheduling with recovery resources. IISE Trans 49(10):942–955. https://doi.org/10.1080/24725854.2017.1325027
Barbagallo S, Corradi L, De Ville De Goyet J, Iannucci M, Porro I, Rosso N, Testi A, (2015) Optimization and planning of operating theatre activities: an original definition of pathways and process modeling. BMC Med Inform Decis Mak 15(1):1–16. https://doi.org/10.1186/s12911-015-0161-7
Barnhart C, Johnson EL, Nemhauser GL, Savelsbergh MWP, Vance PH (1998) Branch-and-price: column generation for solving huge integer programs. Oper Res 46(3):316–329
Barz C, Rajaram K (2015) Elective patient admission and scheduling under multiple resource constraints. Product Oper Manag 24(12):1907–1930. https://doi.org/10.1111/poms.12395
Bastian N, Grannan B, Fulton L (2015) Optimizing forward surgical team operating room scheduling for mass casualty events. In: Borchers B, Brooks JP, McLay L (eds) Proceedings of the 14th INFORMS computing society conference, operations research and computing: algorithms and software for analytics, pp 161–171
Batun S, Denton BT, Huschka TR, Schaefer AJ (2011) Operating room pooling and parallel surgery processing under uncertainty. INFORMS J Comput 23(2):220–237. https://doi.org/10.1287/ijoc.1100.0396
Beliën J, Demeulemeester E (2007) Building cyclic master surgery schedules with leveled resulting bed occupancy. Eur J Oper Res 176(2):1185–1204. https://doi.org/10.1016/j.ejor.2005.06.063
Beliën J, Demeulemeester E (2008) A branch-and-price approach for integrating nurse and surgery scheduling. Eur J Oper Res 189(3):652–668. https://doi.org/10.1016/j.ejor.2006.10.060
Beliën J, Demeulemeester E, Cardoen B (2009) A decision support system for cyclic master surgery scheduling with multiple objectives. J Sched 12(2):147–161. https://doi.org/10.1007/s10951-008-0086-4
Belien J, Demeulemeester E (2005) Integrating nurse and surgery scheduling. DTEW Res Rep 0526(2002):1–28. https://lirias.kuleuven.be/bitstream/123456789/228400/1/0526.pdf
Berg BP, Denton BT (2017) Fast approximation methods for online scheduling of outpatient procedure centers. INFORMS J Comput 29(4):631–644. https://doi.org/10.1287/ijoc.2017.0750
Bhattacharyya T, Vrahas MS, Morrison SM, Kim E, Wiklund RA, Smith RM, Rubash HE (2006) The value of the dedicated orthopaedic trauma operating room. J Trauma Acute Care Surg 60(6):1336–1340. https://doi.org/10.1097/01.ta.0000220428.91423.78
Bilgin B, Demeester P, Misir M, Vancroonenburg W, Vanden Berghe G (2012) One hyper-heuristic approach to two timetabling problems in health care. J Heuristics 18(3):401–434. https://doi.org/10.1007/s10732-011-9192-0
Blake JT, Carter MW (2002) A goal programming approach to strategic resource allocation in acute care hospitals. Eur J Oper Res 140(3):541–561. https://doi.org/10.1016/S0377-2217(01)00219-3
Blake JT, Donald J, Ball S (2002) Mount Sinai hospital uses integer programming to allocate operating room time. Interfaces 32(2):63–73. https://doi.org/10.1287/inte.32.2.63.57
Bolduc T (1996) Self-scheduling of the Veteran's Affairs Medical Center's operating room nurses can lead to increased job satisfaction and empowerment (Unpublished doctoral dissertation). Cardinal Stritch University, Milwaukee
Bowers J, Mould G (2004) Managing uncertainty in orthopaedic trauma theatres. Eur J Oper Res 154(3):599–608. https://doi.org/10.1016/S0377-2217(02)00816-0
Brown MJ, Subramanian A, Curry TB, Kor DJ, Moran SL, Rohleder TR (2014) Improving operating room productivity via parallel anesthesia processing. Int J Health Care Qual Assur 27(8):697–706. https://doi.org/10.1108/IJHCQA-11-2013-0129
Bruni ME, Beraldi P, Conforti D (2015) A stochastic programming approach for operating theatre scheduling under uncertainty. IMA J Manag Math 26(1):99–119. https://doi.org/10.1093/imaman/dpt027
Cai XQ, Wu X, Zhou X (2014) Optimal stochastic scheduling, vol 1989. https://doi.org/10.1007/978-1-4899-7405-1
Cardoen B (2011) Operating room planning and scheduling problems: a classification scheme. Int J Health Manag Inf 1(1):1–21

Cardoen B, Demeulemeester E (2008) Capacity of clinical pathways: a strategic multi-level evaluation tool. J Med Syst 32(6):443–452. https://doi.org/10.1007/s10916-008-9150-z
Cardoen B, Demeulemeester E, Beliën J (2009a) Sequencing surgical cases in a day-care environment: an exact branch-and-price approach. Comput Oper Res 36(9):2660–2669. https://doi.org/10.1016/j.cor.2008.11.012
Cardoen B, Demeulemeester E, Beliën J (2009b) Optimizing a multiple objective surgical case sequencing problem. Int J Prod Econ 119(2):354–366
Cardoen B, Demeulemeester E, Beliën J (2010) Operating room planning and scheduling: a literature review. Eur J Oper Res 201(3):921–932. https://doi.org/10.1016/j.ejor.2009.04.011
Carter M, Hans EW, Kolisch R (2012) Health care operations management. OR Spectr 34(2):315–317. https://doi.org/10.1007/s00291-012-0288-1
Castro PM, Marques I (2015) Operating room scheduling with generalized disjunctive programming. Comput Oper Res 64:262–273. https://doi.org/10.1016/j.cor.2015.06.002
Castro E, Petrovic S (2012) Combined mathematical programming and heuristics for a radiotherapy pretreatment scheduling problem. J Sched 15(3):333–346. https://doi.org/10.1007/s10951-011-0239-8
Cayirli T, Veral E (2009) Outpatient scheduling in health care: a review of literature. Product Oper Manag 12(4):519–549. https://doi.org/10.1111/j.1937-5956.2003.tb00218.x
Ceschia S, Schaerf A (2011) Local search and lower bounds for the patient admission scheduling problem. Comput Oper Res 38(10):1452–1463. https://doi.org/10.1016/j.cor.2011.01.007
Ceschia S, Schaerf A (2016) Dynamic patient admission scheduling with operating room constraints, flexible horizons, and patient delays. J Sched 19(4):377–389. https://doi.org/10.1007/s10951-014-0407-8
Chaabane S, Meskens N, Guinet A, Laurent M (2008) Comparison of two methods of operating theatre planning: application in Belgian hospital. J Syst Sci Syst Eng 17(2):171–186. https://doi.org/10.1007/s11518-008-5074-x
Chandoul W, Hammadi S, Camus H, Zgaya H, Di Pompeo C, Trincaretto F (2012) Evolutionary approach for multi-objective scheduling in surgical unit. In: Conférence francophone gestion et ingénierie des systèmes hospitaliers (GISEH 2012)
Chan C, Green L (2013) Handbook of healthcare operations management, vol 184. https://doi.org/10.1007/978-1-4614-5885-2
Chern C-C, Chien P-S, Chen S-Y (2008) A heuristic algorithm for the hospital health examination scheduling problem. Eur J Oper Res 186(3):1137–1157. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0377221707002755https://doi.org/10.1016/j.ejor.2007.02.029
Choi S, Wilhelm WE (2012) An analysis of sequencing surgeries with durations that follow the lognormal, gamma, or normal distribution. IIE Trans Healthc Syst Eng 2(2):156–171. https://doi.org/10.1080/19488300.2012.684272
Choi S, Wilhelm WE (2014a) An approach to optimize block surgical schedules. Eur J Oper Res 235(1):138–148. https://doi.org/10.1016/j.ejor.2013.10.040
Choi S, Wilhelm WE (2014b) On capacity allocation for operating rooms. Comput Oper Res 44:174–184. https://doi.org/10.1016/j.cor.2013.11.007
Conforti D, Guerriero F, Guido R, (2010) A multi-objective block scheduling model for the management of surgical operating rooms: new solution approaches via genetic algorithms. In, (2010) IEEE workshop on health care management. WHCM 2010: https://doi.org/10.1109/WHCM.2010.5441264
Creemers S, Beliën J, Lambrecht M (2012) The optimal allocation of server time slots over different classes of patients. Eur J Oper Res 219(3):508–521. https://doi.org/10.1016/j.ejor.2011.10.045
Day R, Garfinkel R, Thompson S, Day R, Garfinkel R, Thompson S (2012) Integrated block sharing: a win-win strategy for hospitals and surgeons. Manuf Serv Oper Manage 14:567–583. https://doi.org/10.1287/msom.1110.0372
Dekhici L, Khaled B (2010) Operating theatre scheduling under constraints. J Appl Sci 14(10):1380–1388
Denton B, Viapiano J, Vogl A (2007) Optimization of surgery sequencing and scheduling decisions under uncertainty. Health Care Manage Sci 10(1):13–24. https://doi.org/10.1007/s10729-006-9005-4
Denton BT, Miller AJ, Balasubramanian HJ, Huschka TR (2010) Optimal allocation of surgery blocks to operating rooms under uncertainty. Oper Res 58(4–part):1802–816. https://doi.org/10.1287/opre.1090.0791
Derrett S, Devlin N, Hansen P, Herbison P (2003) Prioritizing patients for elective surgery: a systematic review. Int J Technol Assess Health Care 19(1):91–105

Dexter F, Macario A, Traub RD (1999) Which algorithm for scheduling add-on elective cases maximizes operating room utilization? Use of bin packing algorithms and fuzzy constraints in operating room management. Anesthesiol J Am Soc Anesthesiologists 91(5):1491–1491

Dexter F, Traub RD, Macario A (2003) How to release allocated operating room time to increase efficiency: predicting which surgical service will have the most underutilized operating room time. Anesth Analg 96(2):507–512. https://doi.org/10.1097/00000539-200302000-00038

Dexter F, Ledolter J, Wachtel RE (2005) Tactical decision making for selective expansion of operating room resources incorporating financial criteria and uncertainty in subspecialties' future workloads. Anesth Analg 100(5):1425–1432. https://doi.org/10.1213/01.ANE.0000149898.45044.3D

Di Martinelly C, Baptiste P, Maknoon MY (2014) An assessment of the integration of nurse timetable changes with operating room planning and scheduling. Int J Prod Res 52(24):7239–7250. https://doi.org/10.1080/00207543.2014.916827

Díaz-lópez DM, López-valencia NA, González-neira EM (2018) A simulation-optimization approach for the surgery scheduling problem: a case study considering stochastic surgical times. Int J Ind Eng Comput 9:1–14. https://doi.org/10.5267/j.ijiec.2018.1.002

Dios M, Molina-Pariente JM, Fernandez-Viagas V, Andrade-Pineda JL, Framinan JM (2015) A decision support system for operating room scheduling. Comput Ind Eng 88:430–443. https://doi.org/10.1016/j.cie.2015.08.001

Doulabi SHH, Rousseau LM, Pesant G (2016a) A constraint-programming-based branch-and-price-and-cut approach for operating room planning and scheduling. INFORMS J Comput 28(3):432–448. https://doi.org/10.1287/ijoc.2015.0686

Doulabi SHH, Rousseau LM, Pesant G (2016b) Operating room scheduling with generalize disjunctive programming. INFORMS J Comput 28(3):432–448. https://doi.org/10.1287/ijoc.2015.0686

Duma D, Aringhieri R (2018) The management of non-elective patients: shared vs. dedicated policies. Omega (United Kingdom) pp 1–14. Retrieved from https://doi.org/10.1016/j.omega.2018.03.002

Durán G, Rey PA, Wolff P (2017) Solving the operating room scheduling problem with prioritized lists of patients. Ann Oper Res 258(2):395–414. https://doi.org/10.1007/s10479-016-2172-x

Editor S, Hillier FS (2011) Handbook of healthcare system scheduling, 164. https://doi.org/10.1007/978-1-4419-6151-8

Erdem E, Qu X, Shi J (2012) Rescheduling of elective patients upon the arrival of emergency patients. Decis Support Syst 54(1):551–563. Retrieved from https://www.sciencedirect.com/science/article/pii/S0167923612001984https://doi.org/10.1016/j.dss.2012.08.002

Erdogan SA, Denton B (2013) Dynamic appointment scheduling of a stochastic server with uncertain demand. INFORMS J Comput 25(1):116–132. https://doi.org/10.1287/ijoc.1110.0482

Erdogan SA, Denton BT, Cochran JJ (2011) Surgery planning and scheduling. Wiley Encycl Oper Res Manage Sci. https://doi.org/10.1002/9780470400531.eorms0861

Fei H, Chu C, Meskens N, Artiba A (2008) Solving surgical cases assignment problem by a branch-and-price approach. Int J Prod Econ 112(1):96–108. https://doi.org/10.1016/j.ijpe.2006.08.030

Fei H, Chu C, Meskens N (2009) Solving a tactical operating room planning problem by a column-generation-based heuristic procedure with four criteria. Ann Oper Res 166(1):91–108. https://doi.org/10.1007/s10479-008-0413-3

Fei H, Meskens N, Chu C (2010) A planning and scheduling problem for an operating theatre using an open scheduling strategy. Comput Ind Eng 58(2):221–230. https://doi.org/10.1016/j.cie.2009.02.012

Fei H, Meskens N, Chu C (2006) An operating theatre planning and scheduling problem in the case of a "block scheduling" strategy. In: IEEE, pp 1422–428. https://doi.org/10.1109/ICSSSM.2006.320500

Ferrand YB, Magazine MJ, Rao US (2014) Partially flexible operating rooms for elective and emergency surgeries. Decis Sci 45(5):819–847. https://doi.org/10.1111/deci.12096

Ferrand Y, Magazine M, Rao U (2010) Comparing two operating-room-allocation policies for elective and emergency surgeries. In: Proceedings—winter simulation conference, pp 2364–2374. https://doi.org/10.1109/WSC.2010.5678933

Fügener A, Hans EW, Kolisch R, Kortbeek N, Vanberkel PT (2014) Master surgery scheduling with consideration of multiple downstream units. Eur J Oper Res 239(1):227–236. https://doi.org/10.1016/j.ejor.2014.05.009

Fügener A, Schiffels S, Kolisch R (2017) Overutilization and underutilization of operating rooms: insights from behavioral health care operations management. Health Care Manage Sci 20(1):115–128. https://doi.org/10.1007/s10729-015-9343-1

Gartner D, Kolisch R (2014) Scheduling the hospital-wide flow of elective patients. Eur J Oper Res 233(3):689–699. https://doi.org/10.1016/j.ejor.2013.08.026
Gerchak Y, Gupta D, Henig M (1996) Reservation planning for elective surgery under uncertain demand for emergency surgery. Manage Sci 42(3):321–334. https://doi.org/10.1287/mnsc.42.3.321
Guda H, Dawande M, Janakiraman G, Jung KS (2016) Optimal policy for a stochastic scheduling problem with applications to surgical scheduling. Product Oper Manag 25(7):1194–1202. https://doi.org/10.1111/poms.12538
Guerriero F, Guido R (2011) Operational research in the management of the operating theatre: a survey. Health Care Manage Sci 14(1):89–114. https://doi.org/10.1007/s10729-010-9143-6
Guido R, Conforti D (2017) A hybrid genetic approach for solving an integrated multi-objective operating room planning and scheduling problem. Comput Oper Res 87:270–282. https://doi.org/10.1016/j.cor.2016.11.009
Guinet A, Chaabane S (2003) Operating theatre planning. Int J Prod Econ 85(1):69–81. https://doi.org/10.1016/S0925-5273(03)00087-2
Gul S, Denton BT, Fowler JW, Huschka T (2011) Bi-criteria scheduling of surgical services for an outpatient procedure center. Product Oper Manag 20(3):406–417. https://doi.org/10.1111/j.1937-5956.2011.01232.x
Guo M, Wu S, Li B, Rong Y (2014) Maximizing the efficiency of use of nurses under uncertain surgery durations: a case study. Comput Ind Eng 78:313–319. https://doi.org/10.1016/j.cie.2014.04.014
Guo M, Wu S, Li B, Song J, Rong Y (2016) Integrated scheduling of elective surgeries and surgical nurses for operating room suites. Flex Serv Manuf J 28(1–2):166–181. https://doi.org/10.1007/s10696-014-9199-6
Gupta D (2007) Surgical suites' operations management. Prod Oper Manage 16(6):689–700
Hall R.(Ed.) (2012) Handbook of healthcare system scheduling, vol 168. Springer, Boston. Retrieved from http://link.springer.com/10.1007/978-1-4614-1734-7https://doi.org/10.1007/978-1-4614-1734-7
Hamid M, Hamid M, Nasiri MM, Talebi A (2017) A comprehensive mathematical model for the scheduling problem of the elective patients considering all resources and the capacity of the postoperative care unit: a case study. In: International conference on industrial engineering
Hans E, Wullink G, van Houdenhoven M, Kazemier G (2008) Robust surgery loading. Eur J Oper Res 185(3):1038–1050. https://doi.org/10.1016/j.ejor.2006.08.022
Herring WL, Herrmann JW (2012) The single-day surgery scheduling problem: sequential decision-making and threshold-based heuristics. OR Spectr 34(2):429–459. https://doi.org/10.1007/s00291-011-0270-3
Holguín-Veras J, Jaller M, Van Wassenhove LN, Pérez N, Wachtendorf T (2012) On the unique features of post-disaster humanitarian logistics. J Oper Manage 30(7–8):494–506. https://doi.org/10.1016/j.jom.2012.08.003
Holte M, Mannino C (2013) The implementor/adversary algorithm for the cyclic and robust scheduling problem in health-care. Eur J Oper Res 226(3):551–559. https://doi.org/10.1016/j.ejor.2012.10.029
Hosseini N, Taaffe KM (2015) Allocating operating room block time using historical caseload variability. Health Care Manage Sci 18(4):419–430. https://doi.org/10.1007/s10729-014-9269-z
Hsu VN, De Matta R, Lee CY (2003) Scheduling patients in an ambulatory surgical center. Nav Res Logist 50(3):218–238. https://doi.org/10.1002/nav.10060
Huang WT, Chen PS, Liu JJ, Chen YR, Chen YH (2018) Dynamic configuration scheduling problem for stochastic medical resources. J Biomed Inf 80:96–105. https://doi.org/10.1016/j.jbi.2018.03.005
Hulshof PJH, Kortbeek N, Boucherie RJ, Hans EW, Bakker PJM (2012) Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. Health Syst 1(2):129–175. https://doi.org/10.1057/hs.2012.18
Jebali A, Diabat A (2015) A stochastic model for operating room planning under capacity constraints. Int J Product Res 53(24):7252–7270. https://doi.org/10.1080/00207543.2015.1033500
Jebali A, Hadj Alouane AB, Ladet P (2006) Operating rooms scheduling. Int J Prod Econ 99(1–2):52–62. https://doi.org/10.1016/j.ijpe.2004.12.006
Joustra PE, de Wit J, Van Dijk NM, Bakker PJM (2011) How to juggle priorities? An interactive tool to provide quantitative support for strategic patient-mix decisions: an ophthalmology case. Health Care Manage Sci 14(4):348–360. https://doi.org/10.1007/s10729-011-9168-5
Kapamara T, Petrovic D (2009) A heuristics and steepest hill climbing method to scheduling radiotherapy patients. In: Proceedings of the international conference on operational research applied to health services (ORAHS) 1–7 December

Kim K, Mehrotra S (2015) A two-stage stochastic integer programming approach to integrated staffing and scheduling with application to nurse management. Oper Res 63(6):1431–1451. https://doi.org/10.1287/opre.2015.1421

Kim HK, Ao SI, Amouzegar MA (2014) Operating room scheduling problems: a survey and a proposed solution framework. Trans Eng Technol Spec Issue World Congr Eng Comput Sci 2013:1–781. https://doi.org/10.1007/978-94-017-9115-1

Kim SH, Whitt W, Cha WC (2018) A data-driven model of an appointment-generated arrival process at an outpatient clinic. INFORMS J Comput 30(1):181–199. https://doi.org/10.1287/ijoc.2017.0773

Kong Q, Lee CC-Y, Teo C-PC, Zheng Z (2013) Scheduling arrivals to a stochastic service delivery system using copositive cones. Oper Res 61(3):711–726. https://doi.org/10.1287/opre.2013.1158

Koppka L, Wiesche L, Schacht M, Werners B (2018) Optimal distribution of operating hours over operating rooms using probabilities. Eur J Oper Res 267(3):1156–1171. https://doi.org/10.1016/j.ejor.2017.12.025

Kroer LR, Foverskov K, Vilhelmsen C, Hansen AS, Larsen J (2018) Planning and scheduling operating rooms for elective and emergency surgeries with uncertain duration. Oper Res Health Care. Retrieved from https://www.sciencedirect.com/science/article/pii/S2211692317300188https://doi.org/10.1016/J.ORHC.2018.03.006

Lamiri M, Xie X, Dolgui A, Grimaud F (2008b) A stochastic model for operating room planning with elective and emergency demand for surgery. Eur J Oper Res 185(3):1026–1037. https://doi.org/10.1016/j.ejor.2006.02.057

Lamiri M, Xie X, Zhang S (2008c) Column generation approach to operating theater planning with elective and emergency patients. IIE Trans (Inst Ind Eng) 40(9):838–852. https://doi.org/10.1080/07408170802165831

Lamiri M, Grimaud F, Xie X (2009) Optimization methods for a stochastic surgery planning problem. Int J Prod Econ 120(2):400–410. https://doi.org/10.1016/j.ijpe.2008.11.021

Lamiri M, Augusto V, Xie X (2008a) Patients scheduling in a hospital operating theatre. In: 4th IEEE conference on automation science and engineering, CASE 2008, pp 627–632. https://doi.org/10.1109/COASE.2008.4626529

Lamiri M, Dreo J, Xie X (2007) Operating room planning with random surgery times. In: Proceedings of the 3rd IEEE international conference on automation science and engineering, IEEE CASE 2007, pp 521–526. https://doi.org/10.1109/COASE.2007.4341749

Landa P, Aringhieri R, Soriano P, Tànfani E, Testi A (2016) A hybrid optimization algorithm for surgeries scheduling. Oper Res Health Care 8:103–114. https://doi.org/10.1016/j.orhc.2016.01.001

Latorre-Núñez G, Lüer-Villagra A, Marianov V, Obreque C, Ramis F, Neriz L (2016) Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. Comput Ind Eng 97:248–257. https://doi.org/10.1016/j.cie.2016.05.016

Lebowitz P (2003) Schedule the short procedure first to improve OR efficiency. AORN J 78(4):657–659. https://doi.org/10.1016/S0001-2092(06)60671-6

Lee S, Yih Y (2014) Reducing patient-flow delays in surgical suites through determining start-times of surgical cases. Eur J Oper Res 238(2):620–629. https://doi.org/10.1016/j.ejor.2014.03.043

Lehtonen J, Torkki P, Peltokorpi A, Moilanen T (2013) Increasing operating room productivity by duration categories and a newsvendor model. Int J Health Care Qual Assur 26(2):80–92. https://doi.org/10.1108/09526861311297307

Lei L, Lee K, Dong H (2016) A heuristic for emergency operations scheduling with lead times and tardiness penalties. Eur J Oper Res 250(3):726–736. https://doi.org/10.1016/j.ejor.2015.10.005

Li J, Pardalos PM, Sun H, Pei J, Zhang Y (2015) Iterated local search embedded adaptive neighborhood selection approach for the multi-depot vehicle routing problem with simultaneous deliveries and pickups. Expert Syst Appl 42(7):3551–3561. https://doi.org/10.1016/j.eswa.2014.12.004

Li F, Gupta D, Potthoff S (2016) Improving operating room schedules. Health Care Manage Sci 19(3):261–278. https://doi.org/10.1007/s10729-015-9318-2

Liang F, Guo Y, Fung RY (2015) Simulation-based optimization for surgery scheduling in operation theatre management using response surface method. J Med Syst 39(11):159. https://doi.org/10.1007/s10916-015-0349-5

Lim GJ, Mobasher A, Kardar L, Cote MJ (2012) Handbook of healthcare system scheduling, vol 168. https://doi.org/10.1007/978-1-4614-1734-7

Liu Y, Chu C, Wang K (2011) A new heuristic algorithm for the operating room scheduling problem. Comput Ind Eng 61(3):865–871. https://doi.org/10.1016/j.cie.2011.05.020

Ma G, Belien J, Demeulemeester E, Wang L (2011) Solving the strategic case mix problem optimally by using branch-and-price algorithms. In: FBE research report KBI_1107 (Simon 1960) pp 1–33. Retrieved from https://lirias.kuleuven.be/bitstream/123456789/302688/3/KBI_1107[1].pdf
Macario A (2010) What does one minute of operating room time cost? J Clin Anesth 22(4):233–236. https://doi.org/10.1016/j.jclinane.2010.02.003
Macario A, Vitez T, Dunn B, McDonald T (1995) Where are the costs in perioperative care? Analysis of hospital costs and charges for inpatient surgical care. Anesthesiology 83:1138–1144. https://doi.org/10.1097/00132586-199610000-00025
Ma G, Demeulemeester E (2013) A multilevel integrative approach to hospital case mix and capacity planning. Comput Oper Res 40(9):2198–2207. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0305054812000251https://doi.org/10.1016/j.cor.2012.01.013
Magerlein JM, Martin JB (1978) Surgical demand scheduling: a review. Health Serv Res 13(4):418–433. https://doi.org/10.1002/nav.10060
Mancilla C, Storer R (2012) A sample average approximation approach to stochastic appointment sequencing and scheduling. IIE Trans (Inst Ind Eng) 44(8):655–670. https://doi.org/10.1080/0740817X.2011.635174
Marcon E, Dexter F (2006) Impact of surgical sequencing on post anesthesia care unit staffing. Health Care Manage Sci 9(1):87–98. https://doi.org/10.1007/s10729-006-6282-x
Marcon E, Kharraja S, Smolski N, Luquet B, Viale JP (2003) Determining the number of beds in the postanesthesia care unit: a computer simulation flow approach. Anesth Analg 96(5):1415–1423. https://doi.org/10.1213/01.ANE.0000056701.08350.B9
Marques I, Captivo ME (2015) Bicriteria elective surgery scheduling using an evolutionary algorithm. Oper Res Health Care 7:14–26. https://doi.org/10.1016/j.orhc.2015.07.004
Marques I, Captivo ME, Pato MV (2012b) An integer programming approach to elective surgery scheduling. OR Spectr 34(2):407–427. https://doi.org/10.1007/s00291-011-0279-7
Marques I, Captivo ME, Pato MV (2012c) Planning elective surgeries in a Portuguese hospital: study of different mutation rules for a genetic heuristic. Lect Notes Manag Sci 4:238–243
Marques I, Captivo ME, Vaz Pato M (2014) Scheduling elective surgeries in a Portuguese hospital using a genetic heuristic. Oper Res Health Care 3(2):59–72. https://doi.org/10.1016/j.orhc.2013.12.001
Marques I, Captivo ME, Vaz Pato M (2015) A bicriteria heuristic for an elective surgery scheduling problem. Health Care Manag Sci 18(3):251–266. https://doi.org/10.1007/s10729-014-9305-z
Marques I, Captivo ME, Pato MV (2012a) Exact and heuristic approaches for elective surgery scheduling. Congreso Latino-Lberoamericano, Simposio Brasileiro de pesquisa operacional, pp 1880–1891
Matta A, Li J, Sahin E, Lanzarone E, Fowler J (2014) Proceedings of the international conference on health care systems engineering, vol 61. https://doi.org/10.1007/978-3-319-01848-5
May JH, Spangler WE, Strum DP, Vargas LG (2011) The surgical scheduling problem: current research and future opportunities. Product Oper Manag 20(3):392–405
Meskens N, Duvivier D, Hanset A (2013) Multi-objective operating room scheduling considering desiderata of the surgical team. Decis Support Syst 55(2):650–659. https://doi.org/10.1016/j.dss.2012.10.019
M'Hallah R, Al-Roomi AH (2014) The planning and scheduling of operating rooms: a simulation approach. Comput Ind Eng 78:235–248. https://doi.org/10.1016/j.cie.2014.07.022
Min D, Yih Y (2010a) An elective surgery scheduling problem considering patient priority. Comput Oper Res 37(6):1091–1099. https://doi.org/10.1016/j.cor.2009.09.016
Min D, Yih Y (2010b) Scheduling elective surgery under uncertainty and downstream capacity constraints. Eur J Oper Res 206(3):642–652. https://doi.org/10.1016/j.ejor.2010.03.014
Molina-Pariente JM, Fernandez-Viagas V, Framinan JM (2015a) Integrated operating room planning and scheduling problem with assistant surgeon dependent surgery durations. Comput Ind Eng 82:8–20. https://doi.org/10.1016/j.cie.2015.01.006
Molina-Pariente JM, Hans EW, Framinan JM, Gomez-Cia T (2015b) New heuristics for planning operating rooms. Comput Ind Eng 90:429–443. https://doi.org/10.1016/j.cie.2015.10.002
Moosavi A, Ebrahimnejad S (2018) Scheduling of elective patients considering upstream and downstream units and emergency demand using robust optimization. Int J Product Res 120:216–233. https://doi.org/10.1016/j.cie.2018.04.047
Mulholland MW, Abrahamse P, Bahl V (2005) Linear programming to optimize performance in a department of surgery. J Am Coll Surg 200(6):861–868. https://doi.org/10.1016/j.jamcollsurg.2005.01.001
Ng N, Gabriel RA, McAuley J, Elkan C, Lipton ZC (2017) Predicting surgery duration with neural heteroscedastic regression. pp 1–5

Niu Q, Peng Q, ElMekkawy TY (2013) Improvement in the operating room efficiency using Tabu search in simulation. Bus Process Manage J 19(5):799–818. https://doi.org/10.1108/BPMJ-Nov-2011-0081
Ogulata SN, Erol R (2003) A hierarchical multiple criteria mathematical programming approach for scheduling general surgery operations in large hospitals. J Med Syst 27(3):259–270. https://doi.org/10.1023/A:1022575412017
Ogulata SN, Koyuncu M, Karakas E (2008) Personnel and patient scheduling in the high demanded hospital services: a case study in the physiotherapy service. J Med Syst 32(3):221–228. https://doi.org/10.1007/s10916-007-9126-4
Ozkarahan I (1995) Allocation of surgical procedures to operating rooms. J Med Syst 19(4):333–352. https://doi.org/10.1007/BF02257264
Ozkarahan I (2000) Allocation of surgeries to operating rooms by goal programing. J Med Syst 24(6):339–378. https://doi.org/10.1023/A:1005548727003
Pardalos PM, Georgiev PG, Papajorgji P, Neugaard B (eds) (2013) Systems analysis tools for better health care delivery, vol 74. Springer, New York. https://doi.org/10.1007/978-1-4614-5094-8
Paul JA, MacDonald L (2013) A process flow-based framework for nurse demand estimation. Serv Sci 5(1):17–28. https://doi.org/10.1287/serv.1120.0032
Peng Y, Qu X, Shi J (2014) A hybrid simulation and genetic algorithm approach to determine the optimal scheduling templates for open access clinics admitting walk-in patients. Comput Ind Eng 72(1):282–296. https://doi.org/10.1016/j.cie.2014.03.026
Penn ML, Potts CN, Harper PR (2017) Multiple criteria mixed-integer programming for incorporating multiple factors into the development of master operating theatre timetables. Eur J Oper Res 262(1):194–206. https://doi.org/10.1016/j.ejor.2017.03.065
Perdomo V, Augusto V, Xie X (2008) Operating theatre scheduling using Lagrangian relaxation. Eur J Ind Eng 2(2):172–189. https://doi.org/10.1109/ICSSSM.2006.320685
Persson M, Persson JA (2009) Health economic modeling to support surgery management at a Swedish hospital. Omega 37(4):853–863. https://doi.org/10.1016/j.omega.2008.05.007
Persson MJ, Persson JA (2010) Analysing management policies for operating room planning using simulation. Health Care Manage Sci 13(2):182–191. https://doi.org/10.1007/s10729-009-9122-y
Pham DN, Klinkert A (2008) Surgical case scheduling as a generalized job shop scheduling problem. Eur J Oper Res 185(3):1011–1025. https://doi.org/10.1016/j.ejor.2006.03.059
Price C, Golden B, Harrington M, Konewko R, Wasil E, Herring W (2011) Reducing boarding in a post-anesthesia care unit. Product Oper Manag 20(3):431–441. https://doi.org/10.1111/j.1937-5956.2011.01225.x
Pulido R, Aguirre AM, Ibáñez-herrero N, Ortega-mier M (2014) Optimization methods for the operating room management under uncertainty: stochastic programming vs. decomposition approach. J Appl Oper Res 6:145–157
Punnakitikashem P, Rosenberger JM, Buckley Behan D (2008) Stochastic programming for nurse assignment. Comput Optim Appl 40(3):321–349. https://doi.org/10.1007/s10589-007-9084-2
Purnomo HW, Bard JF (2007) Cyclic preference scheduling for nurses using branch and price. Nav Res Logist 54(2):200–220. https://doi.org/10.1002/nav.20201
Qu X, Peng Y, Kong N, Shi J (2013) A two-phase approach to scheduling multi-category outpatient appointments: a case study of a women's clinic. Health Care Manag Sci 16(3):197–216. https://doi.org/10.1007/s10729-013-9223-5
Rachuba S, Werners B (2017) A fuzzy multi-criteria approach for robust operating room schedules. Ann Oper Res 251(1–2):325–350. https://doi.org/10.1007/s10479-015-1926-1
Rath S, Rajaram K, Mahajan A (2017) Integrated anesthesiologist and room scheduling for surgeries: methodology and application. Oper Res 65(6):1460–1478. https://doi.org/10.1287/opre.2017.1634
Razmi J, Yousefi MS, Barati M (2015) A stochastic model for operating room unique equipment planning under uncertainty. IFAC-PapersOnLine 28(3):1796–1801. https://doi.org/10.1016/j.ifacol.2015.06.347
Riise A, Burke EK (2011) Local search for the surgery admission planning problem. J Heuristics 17(4):389–414. https://doi.org/10.1007/s10732-010-9139-x
Riise A, Mannino C, Burke EK (2016) Modelling and solving generalised operational surgery scheduling problems. Comput Oper Res 66:1–11. https://doi.org/10.1016/j.cor.2015.07.003
Rizk C, Arnaout JP (2012) Aco for the surgical cases assignment problem. J Med Syst 36(3):1891–1899. https://doi.org/10.1007/s10916-010-9648-z

Roland B, Di Martinelly C, Riane F, Pochet Y (2010) Scheduling an operating theatre under human resource constraints. Comput Ind Eng 58(2):212–220. https://doi.org/10.1016/j.cie.2009.01.005

Roland B, Di Martinelly C, Riane F (2007) Operating theatre optimization: A resource-constrained based solving approach. In: Proceedings—ICSSSM'06: 2006 international conference on service systems and service management, vol 1, pp 443–448. https://doi.org/10.1109/ICSSSM.2006.320503

Roshanaei V, Luong C, Aleman DM, Urbach D (2017b) Propagating logic-based Benders' decomposition approaches for distributed operating room scheduling. Eur J Oper Res 257(2):439–455. https://doi.org/10.1016/j.ejor.2016.08.024

Roshanaei V, Luong C, Aleman DM, Urbach DR (2017a) Collaborative operating room planning and scheduling. INFORMS J Comput 29(3):558–580. https://doi.org/10.1287/ijoc.2017.0745

Saadouli H, Jerbi B, Dammak A, Masmoudi L, Bouaziz A (2015) A stochastic optimization and simulation approach for scheduling operating rooms and recovery beds in an orthopedic surgery department. Comput Ind Eng 80:72–79. https://doi.org/10.1016/j.cie.2014.11.021

Saremi A, Jula P, Elmekkawy T, Wang GG (2013) Appointment scheduling of outpatient surgical services in a multistage operating room department. Int J Product Econ 141(2):646–658. https://doi.org/10.1016/j.ijpe.2012.10.004

Schedule MS (2006) Block scheduling: toward a master surgical schedule. IEEE 7(6):7. https://doi.org/10.1109/ICSSSM.2006.320501

Schmid V, Doerner KF (2014) Examination and operating room scheduling including optimization of intrahospital routing. Transp Sci 48(1):59–77. https://doi.org/10.1287/trsc.1120.0452

Schütz H-J, Kolisch R (2012) Approximate dynamic programming for capacity allocation in the service industry. Eur J Oper Res 218(1):239–250. https://doi.org/10.1016/j.ejor.2011.09.007

Shylo OV, Prokopyev OA (2012) Stochastic operating room scheduling for high-volume specialties under block booking. INFORMS J Comput 9856:1–11. https://doi.org/10.1287/ijoc.1120.0530

Shylo OV, Prokopyev OA, Schaefer AJ (2013) Stochastic operating room scheduling for high-volume specialties under block booking. INFORMS J Comput 25(4):682–692. https://doi.org/10.1287/ijoc.1120.0530

Silva TAO, De Souza MC, Saldanha RR, Burke EK (2015) Surgical scheduling with simultaneous employment of specialised human resources. Eur J Oper Res 245(3):719–730. https://doi.org/10.1016/j.ejor.2015.04.008

Small TJ, Gad BV, Klika AK, Mounir-Soliman LS, Gerritsen RL, Barsoum WK (2013) Dedicated orthopedic operating room unit improves operating room efficiency. J Arthroplasty 7(1066–1071):e2. https://doi.org/10.1016/j.arth.2013.01.033

Souki M (2011) Operating theatre scheduling with fuzzy durations. J Appl Oper Res 3:177–191

Souki M, Youssef SB, Rebai a (2009) Memetic Algorithm for operating room admissions. In: 2009 international conference on computers and industrial engineering, pp 525–530. https://doi.org/10.1109/ICCIE.2009.5223833

Sperandio F, Gomes C, Borges J, Brito AC, Almada-Lobo B (2014) An intelligent decision support system for the operating theater: a case study. IEEE Trans Autom Sci Eng 11(1):265–273. https://doi.org/10.1109/TASE.2012.2225047

Stull JLW (1991) A comparison of flexible staff scheduling costs to traditional staff scheduling costs for operating room nurses (Unpublished doctoral dissertation). Wright State University, Dayton

Su MC, Lai SC, Wang PC, Hsieh YZ, Lin SC (2011) A SOMO-based approach to the operating room scheduling problem. Expert Syst Appl 38(12):15447–15454. https://doi.org/10.1016/j.eswa.2011.06.016

Tan YY, ElMekkawy TY, Peng Q, Oppenheimer L (2011) Mathematical programming for the scheduling of elective patients in the operating room department. In: Proceedings of the Canadian Engineering Education Association, 10. Retrieved from http://library.queensu.ca/ojs/index.php/PCEEA/article/view/3785

Tànfani E, Testi A (2010) A pre-assignment heuristic algorithm for the master surgical schedule problem (MSSP). Ann Oper Res 178(1):105–119. https://doi.org/10.1007/s10479-009-0568-6

Testi A, Tànfani E (2009) Tactical and operational decisions for operating room planning: efficiency and welfare implications. Health Care Manag Sci 12(4):363–373. https://doi.org/10.1007/s10729-008-9093-4

Testi A, Tanfani E, Torre G (2007) A three-phase approach for operating theatre schedules. Health Care Manag Sci 10(2):163–172. https://doi.org/10.1007/s10729-007-9011-1

Truong VA (2015) Optimal advance scheduling. Manage Sci 61(7):1584–1597

Tsai PFJ, Teng GY (2014) A stochastic appointment scheduling system on multiple resources with dynamic call-in sequence and patient no-shows for an outpatient clinic. Eur J Oper Res 239(2):427–436. https://doi.org/10.1016/j.ejor.2014.04.032

Turhan AM, Bilgen B (2017) Mixed integer programming based heuristics for the patient admission scheduling problem. Comput Oper Res 80:38–49. https://doi.org/10.1016/j.cor.2016.11.016

Valente R, Testi A, Tanfani E, Fato M, Porro I, Santo M, Ansaldo G (2009) A model to prioritize access to elective surgery on the basis of clinical urgency and waiting time. BMC Health Serv Res 9:1. https://doi.org/10.1186/1472-6963-9-1

Valls V, Pérez Á, Quintanilla S (2009) Skilled workforce scheduling in service centres. Eur J Oper Res 193(3):791–804. https://doi.org/10.1016/j.ejor.2007.11.008

Van Der Kooij R, Mes MRK, Hans EW (2015) Simulation framework to analyze operating room release mechanisms. In: 2014 Winter simulation conference, WSC 2014. 2015-January (December) pp 1144–1155. https://doi.org/10.1109/WSC.2014.7019972

van Essen JT, Hans EW, Hurink JL, Oversberg A (2012) Minimizing the waiting time for emergency surgery. Oper Res Health Care 1(2–3):34–44. https://doi.org/10.1016/j.orhc.2012.05.002

van Essen JT, Bosch JM, Hans EW, van Houdenhoven M, Hurink JL (2014) Reducing the number of required beds by rearranging the OR-schedule. OR Spectr 36(3):585–605. https://doi.org/10.1007/s00291-013-0323-x

Van Huele C, Vanhoucke M (2014) Analysis of the integration of the physician rostering problem and the surgery scheduling problem. J Med Syst 38(6):43. https://doi.org/10.1007/s10916-014-0043-z

Van Oostrum JM, Van Houdenhoven M, Hurink JL, Hans EW, Wullink G, Kazemier G (2008) A master surgical scheduling approach for cyclic scheduling in operating room departments. OR Spectr 30(2):355–374. https://doi.org/10.1007/s00291-006-0068-x

Van Riet C, Demeulemeester E (2015) Trade-offs in operating room planning for electives and emergencies: a review. Oper Res Health Care 7:52–69. https://doi.org/10.1016/j.orhc.2015.05.005

van Veen-Berkx E, van Dijk MV, Cornelisse DC, Kazemier G, Mokken FC (2016) Scheduling anesthesia time reduces case cancellations and improves operating room workflow in a university hospital setting. J Am Coll Surg 223(2):343–351. https://doi.org/10.1016/j.jamcollsurg.2016.03.038

Vanberkel PT, Blake JT (2007) A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. Health Care Manag Sci 10(4):373–385. https://doi.org/10.1007/s10729-007-9035-6

Vancroonenburg W, Smet P, Vanden Berghe G (2015) A two-phase heuristic approach to multi-day surgical case scheduling considering generalized resource constraints. Oper Res Health Care 7:27–39. https://doi.org/10.1016/j.orhc.2015.09.010

Vijayakumar B, Parikh PJ, Scott R, Barnes A, Gallimore J (2013) A dual bin-packing approach to scheduling surgical cases at a publicly-funded hospital. Eur J Oper Res 224(3):583–591. https://doi.org/10.1016/j.ejor.2012.09.010

Vissers J, Beech R (2005) Health operations management: patient flow logistics in health care. Psychology Press

Vlah S, Lukač Z, Pacheco J (2011) Use of VNS heuristics for scheduling of patients in hospital. J Oper Res Soc 62(7):1227–1238. https://doi.org/10.1057/jors.2010.73

Wachtel RE, Dexter F (2008) Tactical increases in operating room block time for capacity planning should not be based on utilization. Anesth Analg 106(1):215–226. https://doi.org/10.1213/01.ane.0000289641.92927.b9

Wang JB, Sun L (2010) Single-machine group scheduling with linearly decreasing time-dependent setup times and job processing times. Int J Adv Manuf Technol 49(5–8):765–772. https://doi.org/10.1007/s00170-009-2444-6

Wang XR, Wang JB, Jin J, Ji P (2014) Single machine scheduling with truncated job-dependent learning effect. Optim Lett 8(2):669–677. https://doi.org/10.1007/s11590-012-0579-0

Wang Y, Tang J, Fung RY (2014) A column-generation-based heuristic algorithm for solving operating theater planning problem under stochastic demand and surgery cancellation risk. Int J Product Econ 158:28–36. https://doi.org/10.1016/j.ijpe.2014.07.015

Wang Y, Tang J, Pan Z, Yan C (2015) Particle swarm optimization-based planning and scheduling for a laminar-flow operating room with downstream resources. Soft Comput 19(10):2913–2926. https://doi.org/10.1007/s00500-014-1453-z

Weiss EN (1990) Models for determining estimated start times and case orderings in hospital operating rooms. IIE Trans (Inst Ind Eng) 22(2):143–150. https://doi.org/10.1080/07408179008964166

White DL, Froehle CM, Klassen KJ (2011) The effect of integrated scheduling and capacity policies on clinical efficiency. Product Oper Manag 20(3):442–455. https://doi.org/10.1111/j.1937-5956.2011.01220.x

Wullink G, Van Houdenhoven M, Hans EW, Van Oostrum JM, Van Der Lans M, Kazemier G (2007) Closing emergency operating rooms improves efficiency. J Med Syst 31(6):543–546. https://doi.org/10.1007/s10916-007-9096-6

Xiang W, Yin J, Lim G (2015b) A short-term operating room surgery scheduling problem integrating multiple nurses roster constraints. Artif Intell Med 63(2):91–106. https://doi.org/10.1016/j.artmed.2014.12.005

Xiang W, Yin J, Lim G (2015a) An ant colony optimization approach for solving an operating room surgery scheduling problem. Comput Ind Eng 85:335–345. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S036083521500159Xhttps://doi.org/10.1016/j.cie.2015.04.010

Yahia Z, Harraz N, Eltawil AB (2014) Building master surgery schedules with leveled bed occupancy and nurse workloads. In: IEEE international conference on industrial engineering and engineering management, 2015-January (December), pp 89–93. https://doi.org/10.1109/IEEM.2014.7058606

Zhang Z, Xie X (2015) Simulation-based optimization for surgery appointment scheduling of multiple operating rooms. IIE Trans 47(9):998–1012. https://doi.org/10.1080/0740817X.2014.999900

Zhang B, Murali P, Dessouky MM, Belson D (2009) A mixed integer programming approach for allocating operating room capacity. J Oper Res Soc 60(5):663–673. https://doi.org/10.1057/palgrave.jors.2602596

Zhang Z, Xie X, Geng N (2014) Dynamic surgery assignment of multiple operating rooms with planned surgeon arrival times. IEEE Trans Autom Sci Eng 11(3):680–691. https://doi.org/10.1109/TASE.2013.2267273

Zhao Z, Li X (2014) Scheduling elective surgeries with sequence-dependent setup times to multiple operating rooms using constraint programming. Oper Res Health Care 3(3):160–167. https://doi.org/10.1016/j.orhc.2014.05.003

Zhong L, Luo S, Wu L, Xu L, Yang J, Tang G (2014) A two-stage approach for surgery scheduling. J Comb Optim 27(3):545–556. https://doi.org/10.1007/s10878-012-9535-2

Zhu Z (2011) A two-stage scheduling approach of operation rooms considering uncertain operation time. In: 2011 international conference on information science and technology, ICIST 2011 (pp 1225–1228). https://doi.org/10.1109/ICIST.2011.5765192