Taxonomic Classification of Planning Decisions in Health Care: a Review of the State of the Art in OR/MS

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We provide a structured overview of the typical decisions to be made in resource capacity planning and control in health care, and a review of relevant OR/MS articles for each planning decision. The contribution of this paper is twofold. First, to position the planning decisions, a taxonomy is presented. This taxonomy provides health care managers and OR/MS researchers with a method to identify, break down and classify planning and control decisions. Second, following the taxonomy, for six health care services, we provide an exhaustive specification of planning and control decisions in resource capacity planning and control. For each planning and control decision, we structurally review the key OR/MS articles and the OR/MS methods and techniques that are applied in the literature to support decision making.

Key words: Keywords here

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1. Introduction

Health care managers face the challenging task to organize their processes more effectively and efficiently. The pressure on health care managers rises as both demand for health care and expenditures are increasing steadily [182]. Within a health care organization, managers of different functions jointly organize the health care delivery with the objective to provide high quality care using the limited resources that are available [29]. Designing and organizing processes is known as planning and control, which can be defined as setting goals and deciding in advance what to do, how to do it, when to do it and who should do it. Health care planning and control comprises multiple managerial functions making medical, financial and resource decisions. In this paper we address the managerial function of resource capacity planning and control as defined in [84]: "Resource capacity planning and control addresses the dimensioning, planning, scheduling, monitoring, and control of renewable resources." In general, health care systems are organized in such a way that multiple providers are involved with a patient's treatment. Therefore, to deliver effective and efficient health care, coordinated decision making within a care chain seems promising.

Operations Research and Management Science (OR/MS) is an interdisciplinary branch of applied mathematics, engineering and sciences that uses various scientific research-based principles, strategies, and analytical methods including mathematical modeling, statistics and algorithms to improve an organization's ability to enact rational and meaningful management decisions [126]. OR/MS has been applied widely to resource capacity planning and control in manufacturing. Since the 1950s, the application of OR/MS to health care also yields significant contributions in accomplishing essential efficiency gains in health care delivery. Many different topics have been addressed, such as operating room planning, nurse staffing and appointment scheduling. Due to the interdisciplinary nature of OR/MS applied to health care, there is an extensive base of literature published across various academic fields. Tailored reference databases prove to be valuable in retrieving references from this broad availability. For example, Dexter [57] provides a comprehensive bibliography on operating room management articles. 'ORCHID' [181] is a reference library, which was maintained until 2007 by the Centre for Research in Healthcare Engineering of the University of Toronto and the School of Business Systems of Monash University. The Center for Healthcare Operations Improvement and Research (CHOIR) of the University of Twente introduced and maintains the online literature database 'ORchestra' [180], in which references in the field of OR/MS in health care are categorized by medical and mathematical subject. All the articles mentioned in this review are included and categorized in ORchestra.

NEW CONTRIBUTION

We aim to guide health care managers and OR/MS researchers through the broad field. We provide a structured overview of the typical decisions to be made in resource capacity planning and control in health care, and a review of relevant OR/MS articles for each planning decision.

The contribution of this paper is twofold. First, to position the planning decisions, a taxonomy is presented. This taxonomy provides health care managers and OR/MS researchers with a method to identify, break down and classify planning and control decisions. Our taxonomy contains two axes. The vertical axis reflects the hierarchical nature of decision making in resource capacity planning and control, and the horizontal axis the various health care services. The vertical axis is strongly connected, because higher-level decisions demarcate the scope of and impose restrictions on lower-level decisions. Although health care delivery is generally organized in autonomous organizations and departments, the horizontal axis is also strongly interrelated as a patient pathway often consists of several health care services from multiple organizations or departments.

Second, following the vertical, hierarchical axis of the taxonomy, and for each health care service on the horizontal axis, we provide an exhaustive specification of planning and control decisions in resource capacity planning and control. For each planning and control decision, we structurally review the key OR/MS articles and the OR/MS methods and techniques that are applied in the literature to support decision making. No structured review yet exists of this nature, as existing reviews are typically exhaustive within a confined scope, such as simulation modeling in health care [130] or outpatient appointment scheduling [35], or are general to the extent that they do not focus on the concrete specific decisions.

This paper is organized as follows. Section 2 presents our taxonomy. Section 3 identifies, classifies and discusses the planning and control decisions. Section 4 presents a discussion.

2. Taxonomy

Taxonomy is the practice and science of classification. It origins from biology where it refers to a hierarchical classification of organisms. The National Biological Information Infrastructure [175] provides the following definition of taxonomy: "Taxonomy is the science of classification according to a pre-determined system, with the resulting catalog used to provide a conceptual framework for discussion, analysis, or information retrieval.... A good taxonomy should be simple, easy to remember, and easy to use." With the same objectives, we present a taxonomy for resource capacity planning and control in health care.

Planning and control decisions are made by health care organizations to design and operate the health care delivery process. It requires coordinated long-term, medium-term and short-term decision making in multiple managerial areas. In [84], a framework is presented to subdivide these decisions in four hierarchical, temporal levels and four managerial areas. These hierarchical levels and the managerial area of resource capacity planning and control form the basis of our taxonomy. For the hierarchical levels, [84] applies the well-known breakdown of *strategic*, *tactical* and *operational* [7]. In addition, the operational level is subdivided in *offline* and *online* decision making, where *offline* reflects the in advance decision making and *online* the real-time reactive decision making in response to events that cannot be planned. The four managerial areas are: medical planning, financial planning, materials planning and resource capacity planning. They are defined as follows. *Medical planning* comprises decision making by clinicians regarding for example medical protocols, treatments, diagnoses and triage. *Financial planning* addresses how an organization should manage its costs and revenues to achieve its objectives under current and future organizational and economic circumstances. *Materials planning* addresses the acquisition, storage, distribution and retrieval of all consumable resources/materials, such as suture materials, blood, bandages, food, etc. *Resource capacity planning* addresses the dimensioning, planning, scheduling, monitoring, and control of renewable resources. Our taxonomy is a refinement of the health care planning and control framework of [84] in the resource capacity planning area.

Our taxonomy contains two axes. The vertical axis reflects the hierarchical nature of decision making in resource capacity planning and control, and is derived from [84]. On the horizontal axis of our taxonomy we position the different services in health care. We identify *ambulatory care services*, *emergency care services*, *surgical care services*, *inpatient care services*, *residential care services*, and *home care services*. The taxonomy is displayed in Figure 1. We explain both axes in more detail below.

Vertical structure

Our taxonomy is intended for planning and control decisions to be made within the boundaries of a health care delivery organization. Every health care organization operates in a particular external environment. Therefore, all planning and control decisions are made in the context of this external environment. The external environment is characterized by factors such as legislation, technology and social factors.

The nature of planning and control decision making is such that decisions disaggregate as time progresses and more information becomes available [258]. Aggregate decisions are made in an early stage, while more detailed information supports decision making with a finer granularity in later stages. Because of this disaggregating nature, most well-known taxonomies and frameworks for planning and control are organized hierarchically [84, 258]. As the impact of decisions decreases when the level of detail increases, such a hierarchy also reflects the top-down management structure of most organizations [17].

For completeness we explicitly state the definitions of the four hierarchical levels [84], which we position on the vertical axis of our taxonomy. The definitions are adjusted to specifically fit the managerial area of resource capacity planning and control.

- *Strategic planning* addresses structural decision making. It involves defining the organization's mission (i.e. "strategy" or "direction"), and the decision making to translate this mission into the design, dimensioning, and development of the health care delivery process. Inherently, strategic planning has a long planning horizon and is based on highly aggregated information and forecasts. Examples of strategic planning are determining the facility's location, dimensioning resource capacities (e.g. acquisition of MRI machines,staffing) and deciding on the service mix.
- *Tactical planning* translates strategic planning decisions to facilitate operational planning. While strategic planning addresses structural decision making, tactical planning addresses the organization of the operations/execution of the health care delivery process (i.e. the "what, where, how, when and who"). As a first step in tactical planning, patient groups are characterized based on disease type/diagnose, urgency and resource requirements. As a second step, the available resource capacities, settled at the strategic level, are divided among these patient groups. Optionally, in addition to the allocation in time quantities, more specific timing information can already be added, such as dates or time slots. In this way, blueprints for the operational planning are created that allocate resources to different tasks, specialties and patient groups. While capacity is fixed in operational planning, temporary capacity expansions like overtime or hiring staff are possible in tactical planning. Demand has to be (partly) forecasted, based on (seasonal) demand, waiting list information, and the "downstream" demand in care pathways of patients currently under treatment. Examples of tactical planning are staff shift scheduling and the Master Surgical Schedule (MSS), which is the cyclical schedule that allocates OR time to specialties.
- *Operational planning* (both "offline" and "online") involves the short-term decision making related to the execution of the health care delivery process. Following the tactical blueprints, execution plans are designed at the individual patient level and at the individual resource level. In operational planning, elective demand is entirely known and only emergency demand has to be forecasted. There is low flexibility on this planning level, since decisions on higher levels have demarcated the scope for the operational level decision making.
  - *Offline operational planning* reflects the in advance planning of operations. It comprises the detailed coordination of the activities regarding current (elective) demand. Examples of offline operational planning are patient to appointment assignment, staff to shift assignment and surgical case scheduling.
  - *Online operational planning* reflects the uncertain nature of health care processes demands for reactive decision making. It involves control mechanisms that deal with monitoring the process and reacting to acute events. An example of online operational planning is the real-time dynamic (re)scheduling of patients when an emergency patient requires immediate attention.

A few remarks can be made. First, note that the decision horizon length is not given for any of the hierarchical planning levels, since it depends on the specific characteristics of the application. For example, an emergency department inherently has shorter planning horizons than a long-stay ward in a nursing home. Second, there is a strong interrelation between hierarchical levels. Top-down interaction exists as higher-level decisions demarcate the scope of and impose restrictions on lower-level decisions. Conversely, bottom-up interaction exists as feedback about the health care delivery realization supports decision making in higher levels.

Horizontal structure

On the horizontal axis of our taxonomy we position the different services in health care. The complete spectrum of health care delivery is a composition of many different services provided by many different organizations. From the perspective of resource capacity planning and control, different services may face similar questions. To capture this similarity, we identify a clustering of six care services. The definitions of the six care services are obtained from the MeSH terms provided by PubMed [170]. For each care service we offer several examples of facilities by which this service is provided.

- *Ambulatory care services* provide care to patients without offering a room, a bed and board, and they may be free-standing or part of a hospital. Examples of ambulatory care facilities are outpatient clinics, primary care services and the hospital departments of endoscopy, radiology and radiotherapy.
- *Emergency care services* are concerned with the evaluation and initial treatment of urgent and emergent medical problems, such as those caused by accidents, trauma, sudden illness, poisoning, or disasters. Emergency medical care can be provided at the hospital or at sites outside the medical facility. Examples of emergency care facilities are hospital emergency departments, ambulances and primary care outside office hours.
- *Surgical care services* provide operative procedures (surgeries) for the correction of deformities and defects, repair of injuries, and diagnosis and cure of certain diseases. Examples of surgical care facilities are the hospital's operating theatre, surgical daycare centers and anesthesia facilities.
- *Inpatient care services* provide care to hospitalized patients by offering a room, a bed and board. Examples are nursing wards, intensive care units and neonatal care unit.
- *Residential care services* provide supervision and assistance in activities of daily living with medical and nursing services when required. Examples are nursing homes, rehabilitation clinics with overnight stay and homes for the aged.
- *Home care services* are community health and nursing services provide multiple, coordinated services to a patient at the patient's home. Home care services are provided by a visiting nurse, home health agencies, hospitals, or organized community groups using professional staff for health care delivery. Examples are medical care at home, housekeeping support and personal hygiene assistance.

Again a few remarks can be made. First, note that the horizontal subdivision is not based on health care organizations, but on the provided care services. Therefore, it is possible that a single health care organization offers services in multiple clusters. In addition, a particular facility may belong to multiple care services, for example an MRI scanner that is used in both ambulatory and emergency care services. Second, a patient's treatment often comprises of consecutive care stages offered by multiple care services. The health care delivery realization within one care service is impacted by decisions in other services, as inflow and throughput strongly depends on these other services. Therefore, resource capacity planning and control decisions are always made in the context of decisions made for other care services. Hence, like the interrelation in the vertical levels, a strong interrelation exists between the horizontal clusters.

This taxonomy provides a method to identify, break down and classify planning and control decisions in health care. This enables the acquirement of a complete specification of planning decisions and helps to gain understanding of the interrelations between various planning decisions. Hence, health care managers can identify lacking, insufficiently defined and incoherent planning decisions within their department or organization. It also enables to identify planning decisions

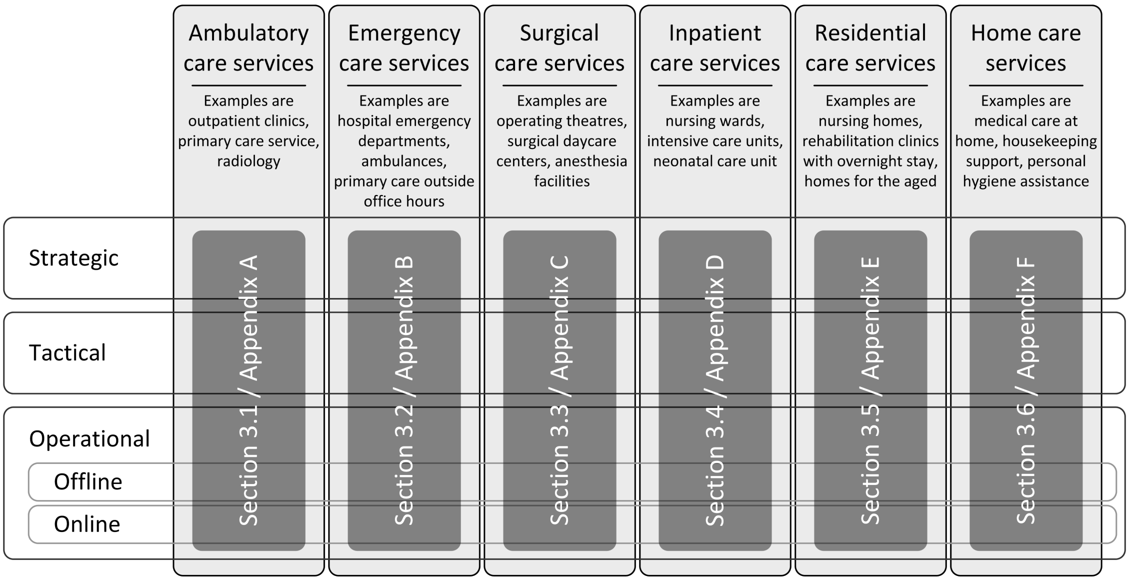

Figure 1 Taxonomy: the hierarchical levels and care clusters in resource capacity planning and control decisions in health care.

that are not yet addressed often in the OR/MS literature. Therefore, in Section 3, with our taxonomy as the foundation, we provide a comprehensive specification of planning decisions for each care service.

3. Identification and classification of planning and control decisions

In this section, for each of the six care services in our taxonomy, we devote a subsection to identify the resource capacity planning and control decisions for this care service. The decisions are classified according to the vertical hierarchical structure of our taxonomy. For each identified planning decision we will discuss the following in our overview:

- What is the concrete *decision*?
- Which *performance measures* are considered?
- What are the *key trade offs*?
- What are *main insights and results* from the literature?
- Which *OR/MS methods* are applied to support decision making?
- What are *general conclusions*?

The identified planning decisions are in the first place obtained from available books and articles on health care planning and control. Our literature search method will be explained in more detail below. In addition, expert opinions from health care managers and OR/MS specialists are obtained to identify decisions that are not yet well-addressed in the literature. In this introduction, we first discuss the scope of the identified planning decisions and the applied OR/MS methods, and next we present the applied literature search method.

Scope. Numerous processes are involved in realizing health care delivery. We focus on the resource capacity planning and control decisions to be made regarding the *primary process* of health care delivery. In management literature, the primary process is defined as the set of activities that are directly concerned with the creation or delivery of a product or service [189]. We do not focus on *supporting activities*, such as procurement, information technology, human resource management, laboratory services, blood services and instrument sterilization.

We focus on OR/MS methods that quantitatively support and rationalize decision making in resource capacity planning and control. Based on forecasting of demand for care (see [183] for forecasting techniques), these methods provide optimization techniques for the design of the health care delivery process. Outside our scope is statistical comparison of performance of health care organizations, so-called benchmarking, of which Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are well-known examples [43]. Quantitative decision making requires measurable performance indicators by which the quality of health care delivery can be expressed. Li and Benton [155] provide a comprehensive survey of applied performance measures in health care organizations. The spectrum of different OR/MS methods is wide (see for example [119, 220, 226, 253]) for introductory books). In this review, we distinguish the following OR/MS methods: mathematical programming [184, 206], Markov processes (which includes Markov reward and decision processes) [226], queueing processes [201], computer simulation [152] and (meta)heuristics [1].

Literature search method. As the body of literature on resource capacity planning and control in health care is extensive, we use a structured search method and restrict to articles published in ISI-listed journals to ensure that we find and filter key and state-of-the-art contributions. Table 1 displays our search method. To identify the search terms and to create the basic structure of the planning decision hierarchy for each care service, we consulted available literature reviews [20, 27, 28, 31, 34, 35, 40, 81, 90, 91, 104, 107, 108, 127, 130, 145, 161, 167, 188, 190, 214, 228, 236] and books [29, 110, 150, 169, 183, 242]. Additional search terms are obtained from the index of *Medical Subject Headings* (MeSH) [170] and available synonyms. With these search terms, we perform a search on the database of Web of Science (WoS) [246]. WoS is chosen as it contains articles from all ISI-listed journals. It is particularly useful as it provides the possibility to select *Operations Research and Management Science* as a specific subject category and to sort references on the number of citations.

We identify a base set containing the ten most-cited articles in the predefined subject category of *Operations Research and Management Science*. Starting from this base set, we include all articles from ISI-listed journals that are referred by and refer to one of the articles in the base set and deal with resource capacity planning and control decisions. As such, we ensure that we also review recent work that may not have been cited often yet. In addition, we include articles published in Health Care Management Science (HCMS), which is particularly relevant for OR/MS in health care and recently obtained an ISI listing. To be sure that by restricting to WoS and HCMS, we do not neglect essential references, we also performed a search with our search terms on the databases of Business Source Elite [78], PubMed [191] and Scopus [207]. This search did not result in significant additions to the already found set of papers. The literature search was updated until 04-01-2011.

Step 1:	Identify search terms from reviews, books and MeSH
Step 2:	Search the OR/MS subject category in WoS with the search terms
Step 3:	Select a base set: the ten most-cited articles relevant for our review
Step 4:	Perform a backward and forward search on the base set articles
Step 5:	Search relevant articles from HCMS

Table 1 The search method applied to each care service.

3.1. Ambulatory care services

Strategic planning

Regional coverage. Ambulatory care planning on a regional level aims to create the infrastructure to provide health care to the population in its catchment area. This *regional coverage* decision involves determining the number, size and location of facilities in a certain region to find a balanced distribution of facilities with respect to the geographical location of demand [75]. The main trade-off in this decision is between patient accessibility and efficiency. Patient accessibility is represented by access time and travel distance indicators. Efficiency is represented by utilization and productivity indicators. Common regional planning models incorporate the dependency of demand on the regional demographic and socio-economic characteristics.
Methods: Computer simulation [166, 199, 216, 225], heuristics [2, 75].

Service mix. In general, the service mix decision is not made at an ambulatory care service level, but at the hospital level, as it integrally impacts the ambulatory, emergency, surgical and inpatient care services. This is also expressed by [241] in which for example inpatient resources, such as beds and nursing staff, are indicated as 'following' resources. This may be the reason that we have not found any references focusing on service mix decisions for ambulatory care services in specific.
Methods: -

Case mix. Every ambulatory care facility decides on a particular case mix, which is the volume and composition of patient groups that the facility serves. Patient groups can be classified based on disease type, age, acuteness, home address, etc. The case mix influences almost all other planning decisions, such as a facility's location, its capacity dimensions and its layout. Also, demand for different patient groups in the case mix may vary, which influences required staffing levels significantly [213, 218]. However, case mix decision making not seems to have received much attention in the literature. Often, the case mix is treated as given.

Methods: Computer simulation [218], mathematical programming [213].

Panel size. The panel size is the number of potential patients of an ambulatory care facility [101]. Since only a fraction of these potential patients, also called calling population, actually demands health care, the panel size can be larger than the number of patients a facility can serve. The panel size is particularly important for general practitioners, as they need an accurate approximation of how many patients they can subscribe or admit to their practice. A panel size should be large enough to have enough demand to be profitable and to benefit from economies of scale, as a facility's costs per patient decrease when the panel size increases [216]. On the other hand, when the panel size is too large, access times may grow exponentially [101].

Methods: Computer simulation [216], queueing processes [101].

Capacity dimensioning. Ambulatory care facilities dimension their resources, such as staff, equipment and space, with the objective to (simultaneously) maximize clinic profit, patient satisfaction, and staff satisfaction [218]. To this end, provider capacity must be matched with patient demand, such that performance measures such as costs, access time and waiting time are controlled. Capacity dimensioning is studied for the following resource types:

- The number of *consultation rooms* that balances patient waiting times and doctor idle time with costs for consultation rooms [218, 219].
- *Staff*, for example doctors, nurses and assistants [16, 130, 166, 213, 216, 218, 219, 250].
- The *consultation time capacity*, for example for MRI or a doctor [48, 79, 80].
- *Equipment*, for example MRI scanners, CT scanners and radiotherapy machines [166, 225].
- The size of the *waiting room* to cope with patients and their companions waiting for consultation [218].

When capacity is dimensioned to cover average demand, variations in demand may cause long access and waiting times [225]. Basic rules from queueing theory demonstrate the necessity of excess capacity to cope with uncertain demand [99]. Capacity dimensioning is a key decision, as it influences how well a facility can meet demand and manage access and waiting times.

Methods: Computer simulation [79, 80, 166, 216, 218, 219, 225, 250], mathematical programming [213], queueing processes [16, 48, 80], literature review [130].

Patient routing. Ambulatory care for a patient typically consists of multiple stages. We denote the sequence of these stages as the route of a patient. An effective and efficient patient route should match medical requirements, capacity requirements and restrictions, and the facility's layout. For a single facility, identifying different patient types and design customized patient routes for each type prevents unnecessary stages and delays [166]. For example, instead of two visits to a doctor and a medical test in between, a patient may undergo a medical test before visiting the doctor, which saves valuable time. Performance is typically represented by total visit time, waiting time, and queue length.

Methods: Computer simulation [39, 166, 216], queueing processes [259].

Facility layout. The facility layout concerns the positioning of different physical areas in a facility. A typical ambulatory care facility consists of a reception area, a waiting area, and consultation rooms [94]. The facility layout is an important and perhaps cost-saving decision in ambulatory care facilities [94, 183], but we found no papers that used an OR/MS approach to study the layout of an ambulatory care facility. However, the handbook [183] discusses heuristics for facility layout problems.

Method: Heuristics [183].

Access policy. Waiting list management in appointment driven facilities deals with prioritizing waiting lists so that access time is equitably distributed over patient groups. The traditional approach considers one queue for each doctor, but when patient queues are pooled into one joint queue, patients can be treated by the first available doctor, which reduces access times [238]. Another policy is to treat patients without a scheduled appointment, also called 'walk-in' service. In between scheduled and walk-in service is 'advanced access' (also called 'open access', or 'same-day scheduling'). With advanced access, a facility leaves a fraction of the appointment slots vacant for patients that request an appointment on the same day or within a couple of days. The logistical difficulty of both walk-in service and advanced access is a greater risk of resource idle time, since patient arrivals are more uncertain. However, implementation of advanced access scheduling can provide significant benefits to patient waiting time, doctor idle time and doctor overtime, when the probability of patients not showing up is relatively large [198]. A proper balance between traditional appointment planning and walk-in/advanced access further decreases access times and increases utilization [196, 259]. The specification of such a balanced design is a tactical planning decision, which will be discussed later in this section.

Methods: Computer simulation [9, 88, 196, 238], queueing processes [198, 259].

Tactical planning

Capacity allocation. On the tactical level, resource capacities settled on the strategic level are subdivided over all patient groups. To do so, patient groups are first assigned to resource types.

- *Assign patient groups to resource types.* The assignment of patient groups to available resources requires knowledge about the capabilities of for example clinical staff, support staff or medical equipment, and the medical characteristics of patients. A model is presented in [213] that maximizes the number of patients served by calculating the optimal assignment of patient groups to appropriately skilled members of clinical staff. Efficiency gains are possible when certain tasks can be substituted between clinical staff, either horizontally (equally skilled staff) or vertically (lower skilled staff) [214].

- *Time subdivision.* The available resource capacity, such as staff and equipment, is subdivided over patient groups. For example, general practitioners divide their time between consulting patients and performing prevention activities for patients. When the beneficial effects of prevention can be approximated, the optimal subdivision of capacity can be determined [106]. When patient demand changes over time (e.g., seasonality), a dynamic subdivision of capacity, updated based on current waiting lists, already planned appointments and expected requests for appointments, performs better than a long-term, static subdivision of resource capacity [239].

Methods: Computer simulation [239], mathematical programming [106, 213].

Temporary capacity change. Patient access times may be improved when resource capacity can temporarily be increased or decreased, to cope with fluctuations in patient demand [239]. In [239] a method to adjust a CT scanner's opening hours on the medium term is presented. In [80], the authors determine the required temporary increase in doctor consultation time to decrease patient access times to a certain level. Scheduling staff in a flexible way can provide the desired additional capacity needs [183].

Methods: Computer simulation [80, 239].

Staff shift scheduling. Shifts are hospital duties with a start and end time [31]. Shift scheduling deals with the problem of selecting what shifts are to be worked and how many employees should be assigned to each shift to meet patient demand [81]. More attractive schedules promote job satisfaction, increase productivity, and reduce turnover.

While staff dimensioning on the strategic level has received much attention, shift scheduling in ambulatory care facilities seems underexposed in the literature. In [30] shift schedules are developed for physicians, who often have disproportionate leverage to negotiate employment terms, because of their specialized skills. Hence, physicians often have individual arrangements that vary by region, governing authority, seniority, specialty and training. Although these individual arrangements impose requirements to the shift schedules, there is often flexibility for shifts of different lengths and different starting times to cope with varying demand during the day or during a week. In this context, the handbook [183] discusses staggered shift scheduling and flexible shift scheduling. In the first alternative, employees have varying start and end times of a shift, but always work a fixed number of hours per week. In the latter, cheaper alternative, a core level of staff is augmented with daily adjustments to meet patient demand. The literature on shift scheduling and assignment in health care mainly concerns inpatient care services [81], which we address in Section 3.3.

Method: mathematical programming [30], literature review [31, 81, 183].

Patient admission control. Patient admission control involves the rules according to which patients are selected to be admitted from a waiting list. Factors that are taken into account are for example resource availability, current waiting lists and expected demand. Clearly, this makes patient admission control and capacity allocation mutually dependent. This is for example the case in the CT scanner capacity subdivision in [239], where the subdivision is settled by determining the number of patients to admit from each patient group. Access times can be controlled by adequate patient admission control [129, 239]. Patient admission control plays a significant role in advanced access or walk-in policies (discussed in the strategic level planning decision of *access policy*). Successful implementation of these policies requires a balance between the reserved and demanded number of slots for advanced access or walk-in patients. Too many reserved slots results in resource idle time, and too little reserved slots results in increased access time. This trade off is modeled in [193] to determine the optimal percentage of reserved slots.

Methods: Computer simulation [239], mathematical programming [129], probability theory [193].

Appointment scheduling. Appointment schedules are blueprints that can be used to provide a specific time and date for patient consultation (e.g., an MRI scan or a doctor visit). Appointment scheduling comprises the design of such appointment schedules. Typical objectives of this design are to minimize patient waiting time, maximize resource utilization or minimize resource overtime. A key trade off in appointment scheduling is the balance between patient waiting time and resource waiting time [120], where it is often assumed that resource waiting time is more costly [35]. In ambulatory care services, appointment scheduling has received the most attention from the literature, which is comprehensively reviewed in [35, 108]. In an early paper, Bailey and Welch [249] present the Bailey-Welch appointment scheduling rule, which is a robust and well-performing rule in many settings [120, 131, 139]. References differ in the extent in which various aspects are incorporated in the applied models. Frequently modeled aspects that influence the performance of an appointment schedule are patient punctuality [88, 154], patients not showing up ('no-shows') [88, 89, 121, 131], walk-in patients or urgent patients [9, 88, 196, 259], doctor lateness at the start of a consultation session [88, 89, 158], doctor interruptions (e.g., by comfort breaks or administration) [89, 154] and the variance of consultation duration [120]. These factors can be taken into account when modeling the following key decisions that together design an appointment schedule.

- *Number of patients per consultation session.* The number of patients per consultation session is chosen to control patient access times and patient waiting times. When the number of patients is increased, access times may decrease, but patient waiting times tend to increase [88, 120].
- *Patient overbooking.* Patients not showing up, also called 'no-shows', cause unexpected gaps, and thus increase resource idleness [120]. Overbooking of patients, i.e., booking more patients into a consultation session than the number of planned slots, is suggested to compensate no-shows in [140, 144, 153, 174, 215]. Overbooking can significantly improve patient access times and provider productivity, but it may also increase patient waiting time and staff overtime [140, 144]. Overbooking particularly provides benefits for large facilities with high no-show rates [140].
- *Length of the appointment interval.* The decision for the length of the planned appointment interval or slot affects resource utilization and patient waiting times. When the slot length is decreased, resource idle time decreases, but patient waiting time increases [89]. For some distributions of consultation time, patient waiting times and resource idle time are balanced when the slot length equals the expected length of a consultation [35]. The slot length can be chosen equal for all patients [120, 89, 249], but using different, appropriate slot lengths for each patient group may decrease patient waiting time and resource idle time when expected consultation times differ between patient groups [79].
- *Number of patients per appointment slot.* Around 1960, it was common to schedule all patients in the first appointment slot of a consultation session [92]. This minimizes resource idle time, but has a major negative effect on patient waiting times [188]. Later, it became common to distribute patients evenly over the consultation session to balance resource idle time and patient waiting time. In [92] various approaches in between these two extremes are evaluated, such as two patients in one time slot and zero in the next.
- *Sequence of appointments.* When different patient groups are involved, the sequence of appointments influences waiting times and resource utilization. Appointments can be sequenced based on patient group or expected variance of the appointment duration. In [139] various rules for patient sequencing are compared. Alternatively, when differences between patients exist with respect to the variation of consultation duration, sequencing patients by increasing variance (i.e., lowest variance first) may minimize patient waiting time and resource idle time [35].
- *Queue discipline in the waiting room.* The queue discipline in the waiting room affects patient waiting time, and the higher a patient's priority, the lower the patient's waiting time. The queue discipline in the waiting room is often assumed to be first-come, first-served (FCFS), but when emergency patients and walk-in patients are involved, highest priority is assumed for emergency patients and lowest priority for walk-in patients [35]. In [166], priority is given to the patient that has to visit the most facilities on the same day, but the authors report that this does not result in a significant benefit to overall performance.
- *Anticipation for unscheduled patients.* Facilities that also serve unscheduled patients, such as walk-in and urgent patients, require an appointment scheduling approach that anticipates these unscheduled patients by reserving slack capacity. This can be achieved by leaving certain appointment slots vacant, or by increasing the length of the appointment interval [35]. Reserving too little capacity for unscheduled patients results in an overcrowded facility, while reserving too many may results in resource idle time. Often, unscheduled patients arrive in varying volumes during the day and during the week. When an appropriate number of slots is reserved for unscheduled patients, and appointments are scheduled at moments that the expected unscheduled demand is low, patient waiting times decrease and resource utilization increases [196, 259]. In the online

operational level of this section, we discuss referring unscheduled patients to a future appointment slot when the facility is overcrowded.

Methods: computer simulation [11, 36, 55, 79, 88, 89, 113, 120, 121, 144, 154, 158, 166, 196, 218, 243, 249], heuristics [131], Markov processes [92, 102, 131, 139, 156, 174], mathematical programming [52, 197], probability theory [215], queueing processes [26, 48, 140, 153, 197, 259], literature review [35, 108, 130].

Offline operational planning

Staff to shift assignment. On the tactical level, staff shift scheduling results in shifts that have to be worked. In staff to shift assignment on the offline operational level, a date and time are given to a staff member to perform a particular shift. For example, a consultation session is scheduled for a doctor on a particular day, time and with a certain duration. For an endoscopy unit, the authors of [129] develop a model to schedule available doctors to endoscopy unit shifts.

Method: Mathematical programming [129].

Patient to appointment assignment. Based on the appointment scheduling blueprint developed on the tactical level, patient scheduling comprises scheduling of an appointment in a particular time slot for a particular patient. A patient may require multiple appointments on one or more days. Therefore, we distinguish scheduling a *single appointment*, *combination appointments* and an *appointment series*.

- *Single appointment.* When patient require an appointment, they often have a preference for certain slots. When information is known about expected future appointment requests and the expected preferences of these requests, a slot can be planned for this patient to accommodate the current patient, but also to have sufficient slots available for future requests from other patients. This can for example be necessary to ensure sufficient slots are available for advanced access patients [109] or to achieve equitable access for all patient groups to a diagnostic facility [185].
- *Combination appointments.* 'Combination' appointments imply that multiple appointments for a single patient are planned on the same day, such that a patient requires fewer hospital visits. We have found no papers that evaluate scheduling of combination appointments.
- *Appointment series.* For some patients, a treatment consisting of multiple (recurring) appointments may span a period of several weeks or months. The treatment is planned in an appointment series, and appointments may have precedence relations and certain minimum and maximum time spanning between them. In addition, the incorporation of multiple resources may further complicate the planning of the appointment series. The appointment series have to fit in the existing appointment schedules, which are partly filled with already scheduled appointments. Examples of patients that require appointment series are radiotherapy patients [45, 46] and rehabilitation patients [41].

Methods: Heuristics [41], Markov processes [109, 185], mathematical programming [45, 46].

Online operational planning

Dynamic patient (re-)assignment. After patients are assigned to slots in the appointment schedule, the appointments are carried out on their planned day. During such a day, acute events, such as emergency or walk-in patients, extended consultation times and equipment breakdown, may disturb the planned appointment schedule. In such cases, real-time dynamic (re)scheduling of patients is required to improve patient waiting times and resource utilization in response to acute events. For example, to cope with an overcrowded facility walk-in patients can be rescheduled to a future appointment slot to improve the balance of resource utilization over time [194]. Dynamic patient (re)scheduling can also be used to decide which patient group to serve in the next time slot in the appointment schedule [102], for example based on the patient groups' queue lengths. When inpatients are involved in such decisions, they are often subject to rescheduling [35], since it is assumed that they are less troubled by a rescheduled appointment as they are already in the hospital. However, longer waiting times of inpatients may be more costly, since it may mean they have to be hospitalized longer [49].

Methods: Computer simulation [194], Markov processes [49, 102, 156], mathematical programming [49].

Dynamic staff (re-)assignment.

Methods: -.

3.2. Surgical care services

There is large number of comprehensive literature reviews in OR/MS applied to surgical care services [20, 34, 57, 104, 107, 108, 161, 167, 190, 244]. These reviews are used to create the basic structure of the planning decisions in this section.

Strategic planning

Regional coverage. At a regional level, the number, types and locations of surgical care facilities have to be decided to find a balanced distribution of facilities with respect to the geographical location of demand [75]. The main trade-off in this decision is between patient accessibility and facility efficiency. Coordination of activities between hospitals in one region, can provide significant cost reductions at surgical care facilities and downstream facilities [24, 203].

Methods: computer simulation [24], mathematical programming [203].

Service mix. Management decides the particular services that the surgical care facility provides. The service mix determines what types of surgeries can be performed, for example specialized surgeries or surgeries for specific patient types, and hence impacts net contribution of a facility [122]. Examples of services are robotic services for assisting specialized surgery [53] and ambulatory services [122]. Ambulatory services include ambulatory surgical wards, where ambulatory patients wait and stay before and after surgery. Ambulatory surgical wards are part of *surgical care services* and not discussed in *inpatient care services*, since outpatients served on ambulatory basis do not require an overnight stay. In general, the service mix decision is not made at a surgical care service level, but at the hospital level, as it integrally impacts the ambulatory, emergency, surgical and inpatient care services.

Methods: -.

Case mix. The case mix involves the number and types of surgical cases that are served at the facility. Often, diagnosis-related groups (DRGs), which represent patient groups with the same diagnosis and thus similar resource requirements, are used to identify the patient types that are included in the case mix [125].

Since surgical care services are the hospital's largest revenue center [34, 54], the case mix is chosen with the objective to optimize net contribution, costs and profit [104]. The case mix decision should balance multiple objectives [21, 104], such as maximizing the number of surgeries performed [21] and maximizing net contribution [125], while considering both internal and external factors. Internal factors are the limited resource capacity, the settled service mix, research focus, and medical staff preferences and skills [21, 104]. External factors are societal preferences, the disease processes affecting the population in the facility's catchment area [21], the case mix of competing hospitals [74], and the restricted budgets and service agreements in government funded systems [21]. High profit patient types may be used to cross-subsidize the unprofitable ones, possibly included for research or societal reasons [21].

Methods: mathematical programming [21, 125], literature review [104].

Capacity dimensioning. Surgical care facilities dimension their resources with the objective to optimize hospital profit, idle time costs, surgery delays, access time for surgery and overtime of staff [159, 205]. Therefore, provider capacity must be matched with patient demand [205] for the following resources:

- *Operating rooms*, possibly specified based on the type of procedure [107, 130, 205].
- *Staff*, including surgeons, anesthesiologists, surgical assistants and nurse anesthetists [4, 53].
- The *operating time capacity*, the number of hours per time period the surgical care services are provided [167, 223, 235]. Operating time capacity is determined by the number of operating rooms and their opening hours [159].
- *Pre-surgical wards*, used for pre-operative activities, for example induction rooms for anesthetic purpose [167].
- *Recovery wards*, where patients recover from surgery [141, 142, 205], also called Post Anaesthesia Care Unit (PACU) [104].
- *Ambulatory surgical ward*, where outpatients stay before and after surgery.
- *Equipment*, required to perform particular surgeries. Examples are imaging equipment [108] or robotic equipment [53]. Equipment may be transferable between rooms, which increases scheduling flexibility.

Staffing costs are a large portion of costs in surgical care services [8, 53]. Significant cost savings can be achieved by increasing staffing flexibility [53], for example by (i) cross-training surgical assistants for multiple types of surgeries [107], (ii) augmenting nursing staff with short-term contract nurses [53], and (iii) drawing nurses from less critical parts in the hospital during demand surges [53].

The capacity dimension decisions for different resource types are interrelated. Performance is improved when these decisions are coordinated both within the surgical care facility and with capacity dimension decisions in ancillary services outside the surgical care facility, such as medical care units and the ICU [204, 235].

Methods: computer simulation [141, 159, 204, 205, 235], heuristics [53], mathematical programming [53, 223], queueing processes [159], literature review [130, 167].

Patient routing. A surgical process consists of multiple stages. We denote the sequence of these stages as the route of a patient. The surgical process consists of a pre-operative, peri-operative and post-operative stage [104, 107, 187]. The pre-operative stage involves waiting and anesthetic interventions, which can take place in induction rooms [164] or in the operating room [167]. The peri-operative stage involves surgery in the operating room, and the post-operative stage involves recovery at a recovery ward [104]. Recovery can also take place in the operating room when a recovery bed is not immediately available [10]. Surgical patients requiring a bed are admitted to a (inpatient or outpatient) medical care unit before the start of the surgical process, where they return after the surgical process [128].

Methods: computer simulation [164], heuristics [10], mathematical programming [10, 187], literature review [104, 167].

Facility layout. The facility layout concerns the positioning and organization of different physical areas in a facility. Hospital managers aim to find the layout of the surgical care facility that maximizes the number of surgeries that can take place, given the budgetary and building constraints. A proper integration of the facility layout decision and the patient routing decision decreases costs and increases the number of patients operated [164]. For example, when patients are not anesthetized in the operating room, but in an adjacent induction room, patients can be operated with shorter switching times in between. In [167], literature contributions that model a facility layout decision for surgical care services are reviewed.

Method: computer simulation [164], literature review [167].

Tactical planning

Capacity allocation. On the tactical level, resource capacities settled on the strategic level are subdivided over sets of patients, classified by (sub)specialty, medical urgency, diagnosis or resource requirements. For these sets of patients, we use the term *patient groups*.

Capacity allocation strategies include *block* scheduling and *open* (or non-block) scheduling. Block scheduling involves the subdivision of blocks of operating time capacity over identified patient groups. Conversely, open scheduling involves no subdivision, but signifies scheduling all patient groups in the available operating time capacity, for example first-come, first-served (FCFS) [104, 107]. Although open scheduling is more flexible than block scheduling, open scheduling is rarely adopted in practice [23, 104], because it leads to different operating time capacity utilization among different patient groups [161, 190]. Block scheduling is commonly used [87, 104], since it increases operating time utilization and the number of surgeries performed per day (due to continuity of operations), decreases competition between surgeons for surgical capacity, and benefits doctor schedules [161, 190].

The objective of capacity allocation is trade off patient access time and the utilization of surgical and post-surgical resources [20, 104, 161, 223]. Other objectives are to maximize contribution margin per hour [34, 60], maximize the number of patients operated, or minimize staff overtime [111].

Capacity is allocated in three consecutive steps. First, patient groups are identified. Second, resource capacities, often in the form of operating time capacity, are subdivided over the identified patient groups. Third, blocks of subdivided capacity are scheduled to a specified date and time.

- *Patient group identification.* Patient groups may be identified by specialty, medical urgency, diagnosis and resource requirements. Identification by medical urgency distinguishes elective, urgent and emergent cases [34, 83, 104, 107]. Elective cases can be planned in advance, urgent cases require surgery urgently, but can incur a short waiting period, and emergency patients require surgery immediately [25, 34]. An example of patient grouping by resource requirements are inpatients, requiring a bed for overnight stay [107], versus outpatients, not requiring an overnight stay. The proportion of outpatient surgeries, which are typically shorter, less complex and less variable [187], is increasing in many hospitals [167].
- *Time subdivision.* The available resource capacity, often in the form of operating time capacity, is subdivided over the identified patient groups. Subdivision of capacity is an important way to maximize efficiency [70] and to achieve an equitable distribution of access time for patients [223].

  In a first step, capacity is reserved for emergency cases, who arrive randomly. Since capacity requirements for emergency cases are random, a balanced reservation is important for balancing resource utilization and staff overtime [147]. When reserved capacity for emergency cases is too low, staff overtime occurs, and when it is too high, resource utilization is low, which causes growth in elective waiting lists [25, 147, 148, 186, 260]. Capacity can be reserved by dedicating one or more operating rooms to emergency cases, or by reserving capacity in elective operating rooms [34, 212]. The latter is preferred in some hospital environments [34, 146]. After capacity is reserved for emergency cases, the remaining capacity can be allocated to elective cases [95].
- *Block scheduling.* In the last step of capacity allocation, a date and time are assigned to blocks of allocated capacity [13]. Several factors have to be considered in developing a block schedule.

For example, (seasonal variation in) surgery demand, the number of operating rooms, workforce capacities, surgeon preferences, material requirements and equipment requirements [13, 203].

Block schedules are often developed to be cyclic, meaning the block schedule can be repeated periodically. A cyclic block schedule is also termed a Master Surgical Schedule (MSS) [234], but definitions of an MSS vary among OR/MS researchers [34]. Cyclic block schedules are suitable for elective procedures that occur quite frequent [234], because relatively rare procedures may not fit typical blocks [104]. Two strategies exist to cope with rare procedures. First, capacity can be reserved in the cyclic block schedule for rare procedures [244]. Second, the use of non-cyclical plans may provide an outcome. When compared to cyclic plans, non-cyclic [53, 67, 68], or variable plans [130], increase flexibility, decrease staffing costs [53] and decrease patient access time [130].

In [241] surgical care services are termed 'leading resources' and inpatient care services are called 'following resources'. From this perspective, capacity allocation decisions in surgical care services impact inpatient care services performance [13, 15, 53]. Variability in bed utilization and staff requirements can be decreased by employing bed utilization knowledge in allocating surgical care capacity [3, 13, 15, 100, 203, 233, 234]. In contributions that model ancillary services, it is often the objective to level bed occupancy in wards or ICU, to decrease the number of cancellations [13, 34, 203, 233, 234], or to minimize delays for inpatients [257]. In [221, 223, 224], capacity dimensioning decisions in ancillary services limit the possible allocations of surgical capacity. Relatively few papers evaluate the effect of surgical care services on ancillary services [161, 20, 34].

Methods: computer simulation [25, 64, 67, 68, 147, 186, 257], heuristics [13, 14, 15, 221, 241], mathematical programming [13, 14, 15, 22, 23, 37, 38, 53, 147, 203, 221, 223, 224, 233, 234, 257], Markov processes [95, 260], queueing processes [260], *miscellaneous* [60], literature review [20, 34, 104, 107, 130, 161, 244].

Temporary capacity change. Available resource capacity could be temporarily changed in response to fluctuations in demand [159]. When additional operating time capacity is available, it can be allocated to a particular patient group, for example based on contribution margin [60, 107, 244] or access times [223], or proportionally subdivided between all patient groups [23, 223].

Methods: computer simulation [64], mathematical programming [23, 53, 223].

Unused capacity (re-)allocation. In many hospitals, when time progresses closer to the date of carrying out a settled block schedule, capacity allocation decisions are reconsidered in order to re-allocate capacity that remains unused and to allocate capacity not allocated before. The factors considered in allocating temporarily added capacity are also considered in the (re-)allocation of unused capacity.

Unused capacity that is allocated to patient groups may become available for other patient groups beyond a given deadline, for example a number of days prior to the scheduled date [72, 107]. *Modified block* scheduling involves allocating a fraction of capacity on the long-term, and allocating the remaining capacity, also called overflow capacity [60, 64], on the mid-term. Re-allocating unused capacity and modified block scheduling both allow allocating capacity closer to the planned date of health care delivery, when more detailed and accurate information is available. Hence, there exists more flexibility to match available resource capacities with fluctuating patient demand [104].

Methods: computer simulation [64, 72], heuristics [72], literature review [107].

Patient admission control. Patient admission control involves the rules according to which patients from different patient groups are selected to be served in the available operating time capacity. Hence, there is a strong relation between patient admission control decisions and capacity allocation decisions. Patient admission control has the objective to balance patient service, high resource utilization, staff satisfaction and costs [20].

Patient admission control is established by developing an admission plan that prescribes how many patients of each patient group to admit on each day [3]. The number of surgical cases per day may be bounded or balanced throughout the week. This prevents high variance in operating time utilization or medical care units on different days [134, 161, 227], but also in ancillary services [3, 13, 134, 227]. For example, balancing the number of elective cases requiring an ICU bed decreases the number of cancellations significantly [134, 227].

Resource utilization can be improved by using call-in patients [20] and overbooking [25]. Call-in patients are given a time frame in which they can be called in for surgery when there is sufficient space available in the surgical schedule. Overbooking of patients involves planning more surgical cases than available operating time capacity to compensate no-shows [13].

Methods: computer simulation [25, 62, 134, 227], Markov processes [171], mathematical programming [3], literature review [20, 104].

Staff shift scheduling. Shifts are hospital duties with a start and end time [31]. Shift scheduling deals with the problem of selecting what shifts are to be worked and how many employees should be assigned to each shift to meet patient demand [81]. The objective of shift scheduling is to generate shifts that minimize the number of staff hours required to cover the desired staffing levels [190]. The desired staffing levels are impacted by the capacity allocation decision. Hence, integrated decision making for capacity allocation and staff shift scheduling minimizes required staff [14]. Staggered shift scheduling implies that employees have varying start and end times of shifts [183]. It can be used to ensure sufficient staff is available and overtime is avoided [23, 63].

Methods: heuristics [58], mathematical programming [14, 30, 73], literature review [190].

Offline operational planning

Staff to shift assignment. In staff to shift assignment, a date and time are given to a staff member to perform a particular shift. The literature on shift scheduling and assignment in health care mainly concerns inpatient care services [81], which we address in Section 3.3.

Methods: -.

Surgical case scheduling. Surgical case scheduling is concerned with identifying a day and time on which a surgical case can be performed. Availability of the patient, a surgeon, an anesthesist, nursing and support staff and an operating room is a precondition [20]. Surgical case scheduling is an offline operational planning decision, since it results in an assignment of individual patients to planned resources and not in blueprints for assigning surgical cases to particular slots.

The objective of surgical case scheduling is often to achieve a high utilization of involved resources, and low patient deferrals, patient cancellations and staff overtime [34, 53, 86, 163, 187]. Other objectives are staff satisfaction and staff waiting time [200], patient satisfaction, waiting time and throughput [34, 128], and post-surgical resource utilization [212].

Surgical case scheduling is impacted by many factors. The execution of a surgical case schedule is affected by uncertainty in the pre-operative stage, case duration, switching times, post-surgical recovery, emergency patient demand, staff unavailability and the start time of surgeons [104, 187]. Restrictions are imposed by the capacity dimensioning and allocation decisions [223]. Hence, in [223], surgical case scheduling is integrated with the capacity allocation decision.

Although surgical case scheduling can be done integrally in one step [10, 66, 67, 87, 161, 187, 200], it is often decomposed in several steps. First, the planned length of a surgical case is decided. Second, a date and an operating room are assigned to a surgical case on the waiting list (also termed *advance scheduling* [161]). Third, the sequence of surgical cases on a specific day is determined [105, 161] (also termed *allocation scheduling* [161]). Fourth, starting times for each surgical case are determined. Below, we explain these four steps in more detail.

- *Planned length of a surgical case.* The planned length of a surgical case is used to reserve operating time capacity in the surgical schedule. Capacity is also reserved for the switching time between between surgical cases, which is used to clean the operating room, to perform anesthetic procedures, or to change a surgical team [71]. When too little or too much time is reserved, staff overtime and patient waiting time occur, or resources incur idle time respectively [71, 179, 247].

  The planned length of a surgical case is largely determined by surgical case duration, which is often estimated for each patient individually [179] and impacted by many factors, such as the involved surgeon's experience, and the acuteness, sex, and age of the patient [59, 179]. When improved surgical techniques decrease surgical case duration, less capacity can be reserved for that surgical case, leading to decreased costs [61].

- *Assigning dates and operating rooms to surgical cases.* Dates and operating rooms are assigned to the elective cases on the surgical waiting list. The main trade-off in this decision is between staff overtime and resource utilization [86, 85, 111, 128]. When too few cases are planned in the available operating time capacity, utilization decreases, leading to longer waiting lists [25]. Conversely, when too many cases are planned in the available operating time capacity, costs increase due to staff overtime. To cope with uncertainty, 'slack' capacity (i.e., buffer capacity) can be reserved to minimize overtime, maximize operating time utilization and maximize the number of surgeries performed [111].

  Assigning dates and operating rooms to surgical cases can be done for a batch of surgical cases at once or for a single case per time. The batch approach is more efficient than the single case approach, because more assignment possibilities can be considered [67].

- *Sequencing of surgical cases.* When the set of surgical cases for a day or for a block is known, these surgical cases are scheduled according to a given sequence. Various priority rules for sequencing surgical cases exist [32, 187, 212]. Sequencing of surgical cases is impacted by doctor preference [104], medical or safety reasons [128], patient convenience [32], and resource restrictions [33].

  Sequencing of surgical cases by a traditional first-come, first serve (FCFS) rule is inefficient [143]. Instead, a longest processing time first (LPTF) rule results in increased room utilization, decreased staff overtime, and increased operational flexibility [20, 141, 143]. When the variation of the surgical case duration is known, sequencing surgical cases based on the order of increasing case duration variation (i.e., lowest variance first) minimizes staff idle time costs, staff overtime costs and patient waiting time [54, 247].

- *Assigning starting times to surgical cases.* The start time of each surgical case is estimated such that the idle time of involved resources is minimized [247]. A key trade-off is between resource utilization and patient waiting time. An early start time will lead to improved resource utilization at the cost of additional waiting time for the patient [52]. The actual start time of a surgical case is impacted by the planned and actual duration of all preceding surgical cases [247], but also the start time of the pre-operative stage [69].

Emergency cases may play a significant role during the execution of the surgical case schedule [104]. Hence, incorporating knowledge about emergency cases, for example predicted demand, in surgical case scheduling decreases staff overtime and patient waiting time [25, 95, 146, 147, 148].

Often, surgical case scheduling is done in isolation. However, efficiency gains may be achieved by also considering ancillary services [34, 128, 187]. For example, without coordination with the Intensive Care Unit (ICU), a scheduled case may be rejected on its day of surgery due to a full ICU [187]. The contributions [10, 87, 122, 162, 172, 187, 205] incorporate ancillary services, such as pre-surgical wards, PACUs and ICUs, in surgical case scheduling.

Methods: computer simulation [8, 25, 61, 64, 66, 67, 70, 83, 141, 143, 146, 147, 205, 224, 247], heuristics [8, 10, 33, 54, 59, 85, 87, 105, 122, 146, 148, 200, 232], Markov processes [95, 107, 171], mathematical programming [10, 32, 33, 38, 52, 53, 54, 85, 86, 87, 105, 128, 146, 147, 148, 163, 186, 187, 200, 212, 223], queueing processes [247] *miscellaneous* [179], literature review [20, 34, 108, 161, 167].

Online operational planning

Emergency case scheduling. Emergency cases requiring immediate surgery are assigned to reserved capacity or to capacity obtained by canceling or delaying elective procedures [234]. It is the objective to operate emergency cases as soon as possible, but also to minimize disturbance of the surgical case schedule [108]. When emergency cases cannot be operated immediately, prioritizing of emergency cases is required to accommodate medical priorities or to minimize average waiting time of emergency cases [65, 187].

Methods: mathematical programming [65, 187].

Surgical case re-scheduling. When the schedule is carried out, acute events, such as emergency patients, extended surgery duration and equipment breakdown may disturb the surgical case schedule [163]. Hence, the surgical case schedule can be reconsidered during the day to mitigate increasing staff overtime, patient waiting time and resource idle time. Re-scheduling may involve moving scheduled surgeries from one operating room to another and delaying, canceling or rescheduling surgeries [56, 163].

Methods: mathematical programming [163], literature review [107, 108].

Dynamic staff (re-)assignment.

Methods: -.

3.3. Inpatient care services

Strategic planning

Regional coverage. On a regional planning level, the number, types and locations of inpatient care facilities have to be decided. To meet inpatient service demand, the available budget needs to be spent such that the population of each geographical area has access to a sufficient supply of inpatient facilities of appropriate nature and within acceptable distance. Consolidated regional coverage planning aims to realize equity of access to care [19, 202]. To achieve this, local and regional bed occupancies need to be balanced with the local and regional probability of admission refusals resulting from a full census. In [202] is decided upon the best number and locations for additional inpatient services of different specialties, given the already existing facilities. The potential pitfall of deterministic approaches as used in [202] is that resource requirements are underestimated and thus false assurances are provided about the expected service level to patients [115].

Methods: computer simulation [115], mathematical programming [202], queueing processes [19].

Service Mix. In general, the service mix decision is not made on an inpatient care service level, but on the hospital level, as it integrally impacts the ambulatory care facilities, the operating theater and the wards. This may be the reason that we have not found any references focusing on service mix decisions for inpatient care services in specific. Health care facilities that offer inpatient care services can provide a more complex mix of services and can accommodate patient groups with more complex diagnoses [214].

Methods: -.

Case Mix. Given the service mix decision, the types and volumes of patients that the facility serves needs to be decided. With respect to the unavailability of OR/MS literature, the same remark applies as for the service mix decision.

Methods: -.

Care unit partitioning. Given the service and case mix decisions, the hospital management has to decide upon the medical care units in which the inpatient care facility is divided. We denote this decision as care unit partitioning. It addresses both the question which units to create and the question which patients groups to consolidate in such care units. Each care unit has its designated staff, equipment and beds (in one or more wards). The objective is to guarantee care from appropriately skilled nurses and required equipment to patients with specific diagnoses, while making efficient use of scarce resources [76, 77, 97, 115, 118, 208, 240].

First, the desirability of opening shared higher-level care units like various Intensive or Medium Care Units should be considered [229]. Second, the general wards need to be specified. Although traditionally, care unit partitioning was done by establishing a care unit for each specialty, or sometimes even more diagnosis specific [214], specialty-based categorization is not necessarily optimal. Increasingly, the possibilities and implications of consolidating inpatient services for care related groups is investigated to gain from the economies-of-scale effect, so-called 'pooling' [254]. For example, many hospitals merge the cardiac and thoracic surgery unit [100] or allow gynecologic patients in an obstetric unit during periods of low occupancy [168]. In such cases, the overflow rules need to be specified on the tactical level. Also, multi-specialty wards can be created for patients of similar length of stay, such as: day-care, short-, week- and long-stay units [208, 240]. Observation and assessment wards that acute patients to be observed for an initial 24-48 hour period [124]. The intention of concentrating emergency activities in one area is to so improve efficiency and to minimize disruption to other hospital services.

One should be cautious with pooling beds for patient groups with diverging service level [100] or nursing [149] requirements. A combined unit would require the highest service and nurse staffing level for all patient groups. As a result, acceptable utilization may be lower than with separate units. Also, pooling gains should be weighted against possible extra costs for installing extra equipment on each bed [149].

To conclude, the question whether to consolidate or separate clinical services from a logistical point of view is one that should be answered for each specific situation, considering demand characteristics but also performance preferences and requirements [115]. Obviously, the care unit partitioning decision is highly interrelated with the capacity dimensioning decisions, to be discussed next.

Methods: computer simulation [76, 77, 97, 115, 124, 208], queueing processes [100, 118, 168, 229, 254], *misc.* [149].

Capacity dimensioning: care unit size. Together with the care unit partitioning, the number of beds of each inpatient care unit size needs to be determined. Care unit size is generally expressed in the number of staffed beds, as this number is taken as a guideline for dimensioning decisions for other resources such as equipment and staff, which will be discussed below. The common objective is to dimension the number of beds of a single medical care unit such that occupancy of beds is maximized while a predefined performance norm is satisfied [98, 176, 178, 195, 252]. The typical performance measure is the percentage of patients that have to be rejected for admission due to lack of bed capacity: the admission refusal rate. Several other consequences of congested wards can be identified, all being a threat to the provided quality of care. First, patients might have to be transferred to another hospital in case of an emergency [44, 135, 165]. Second, patients may (temporarily) be placed in less appropriate units, so-called misplacements [47, 76, 77, 100, 114, 117].

Third, backlogs may be created in emergency rooms or surgical recovery units [42, 97, 100]. Fourth, elective admissions or surgeries may have to be postponed, by which surgical waiting lists may increase [6, 47, 98, 255], which negatively impacts the health condition of (possibly critical) patients [227, 231]. Finally, to accommodate a new admission in critical care units, one may predischarge a less critical patient to a general ward [251].

The number of occupied beds is a stochastic process, because of the randomness in number of arrivals and lengths of stay [137]. Therefore, slack capacity is required and thus hospitals cannot operate at 100% utilization [50, 100]. Often, inpatient care facilities adopt simple deterministic spreadsheet calculations, leading to an underestimation of the required number of beds [42, 47, 50, 112, 115]. Hospitals commonly apply a fixed target occupance level (often 85%), by which the required number of beds is calculated. Such a policy may result in excessive delays or rejections [100, 115, 137, 176]. The desirable occupancy level should be calculated as a complex function of the service mix, the number of beds and the length of stay distribution [114, 115]. This non-linear relationship between number of beds, mean occupancy level and the number of patients that have to be rejected for admission due to lack of bed capacity is often emphasized [6, 50, 114, 117, 137, 176, 177, 195]. In determining the appropriate average utilization, the effect of economies-of-scale due to the so-called portfolio effect plays a role: larger facilities can operate under a higher occupancy level than smaller ones in trying to achieve a given patient service level [100, 115, 116, 137], since randomness balances out. However, possible economies-of-scope due to more effective treatment or use of resources should not be neglected [100]. Units with a substantial fraction of scheduled patients can in general operate under a higher average utilization [100]. The effect of variability in length of stay on care unit size requirements is shown to be less pressing than often thought by hospital managers [100, 231]. Reducing the average length of stay shows far more potential. For care units that have a demand profile with a clear time-dependent pattern, these effects are preferably explicitly taken into account in modeling and decision making, to capture the seasonal [160, 117], day-of-week [117, 123] or even hour-of-day effects [42, 114]. This is especially for units with a high fraction of emergencies admissions [214].

Capacity decisions regarding the size of a specific care unit can affect the operations of other units. Therefore, capacity among interdependent inpatient care units needs to be balanced [6, 42, 115, 118, 124, 165, 214]. Models that consider only a single unit neglect the possibility of admitting patients in a less appropriate care unit and thus the interaction between patient flows and the interrelationship between care units. In addition to estimating utilization and the probability of admission rejections or delays, models that do incorporate multiple care units, also focus on the percentage of time that patients are placed in a care unit of a lower level or less appropriate care unit, or in a higher level care unit [44, 96, 100, 208]. The first negatively impacts quality of care as it can lead to increased morbidity and mortality [227] and the second negatively impacts both quality of care, as it may block admission of another patient, and efficient use of scarce resources [100, 208]. Some multi-unit models explicitly take the patient's progress through multiple treatment or recovery stages into account and try dimension the care units such that patients can in each stage be placed in the specific care units that are most suitable regarding their physical condition [42, 44, 50, 124, 165, 208, 229].

Methods: computer simulation [6, 42, 44, 47, 76, 77, 97, 112, 115, 116, 124, 135, 165, 176, 177, 178, 195, 208, 227, 251, 252], Markov processes [6, 117, 160], mathematical programming [96], queueing processes [42, 50, 100, 118, 123, 135, 195]

Capacity dimensioning: equipment. No references have been found explicitly focussing on this planning decision. This might be explained by the fact that the care unit partitioning and size decisions are generally assumed to be translatable in equipment capacity requirements (REF?). However, [240] claims that pooling equipment among care units can be highly beneficial.

Methods: -.

Capacity dimensioning: staff. The highest level of personnel planning is the long term workforce capacity dimensioning decision. This decision concerns both the number of employees that have to be employed, often expressed in the number of full time equivalents, and the mix in terms of skill categories. For inpatient care services it mainly concerns nurse staffing. To deliver high-quality care, the workforce capacity needs to be such that an appropriate level of staff can be provided in the different care units in the hospital [81, 96]. In addition, holiday periods, training, illness and further education need to be addressed [31].

Workforce flexibility is indicated as a powerful concept in reducing the required size of workforce [31, 96, 214]. To adequately respond to patient demand variability and seasonal influences, it pays off to have substitution possibilities of different employee types, use part-time employees, use overtime and temporary agency employees [214]. Just as with pooling bed capacity, economies-of-scale can be gained when pooling nursing staff among care units. Nurses cross-trained to work in more than one unit can be placed in a so called floating nurse pool [31, 96, 149, 214]. Note that flexible staff can be significantly more expensive [103]. Also, [151] indicates that to maintain the desired staff capacity it is necessary to determine the long-term human resource planning strategies with respect to recruiting, promotion and training. To conclude, integrating the staff capacity dimensioning decision with the care unit size decision might yield a significant efficiency gain [96].

Methods: computer simulation [103], mathematical programming [96, 151], *misc.* [149], literature review [31, 81, 188, 214].

Facility layout. To determine the inpatient care facility lay-out, it needs to be specified which care units should be next to each other and which care units should be close to other services like the surgical, emergency and ambulatory care facilities. Ideally, the optimal physical layout of an inpatient care facility is determined given the decisions on service mix, case mix, care unit partitioning and care unit size. However, in practice, it often happens vice versa: physical characteristics of a facility constraint service mix, care unit partitioning and care unit size decisions [240]. Explicit OR/MS contributions have not been found for this decision. Newly built hospitals are preferably designed such that they support resource pooling and have modular spaces so that they are as flexible as possible with respect to care unit partitioning and dimensioning [240].

Methods: -.

Tactical planning

Bed reallocation. Given the strategic decision making, tactical resource allocation needs to ensure that the fixed capacities are employed such that inpatient care is provided to the right patient groups at the right time, while maximizing resource utilization. Bed reallocation is the first step in tactical inpatient care service planning. Medium term demand forecasts may expose that the care unit partitioning and size decisions fixed at the strategic level are not optimal. If the ward layout is sufficiently flexible, a reallocation of beds to units or specialties based upon more specific demand forecast can beneficial [12, 114, 241]. In addition, demand forecasts can be exploited to realize continuous reallocation of beds in anticipation for seasonality in demand [132]. Therefore, hospital bed capacity models should incorporate monthly, daily and hourly demand profiles and meaningful statistical distributions that capture the inherent variability in demand and length of stay [112]. When reallocating beds, the implications for personnel planning and costs for bed capacity changing should not be overlooked [5].

Methods: computer simulation [114, 132], heuristics [241], mathematical programming [5, 12], queueing processes [132].

Temporary bed capacity change. To prevent superfluous staffing of beds, beds can temporarily be closed by reducing staff levels [100]. This may for instance be a response to predicted seasonal [112] or weekend demand [116] effects. The impact of such closings on the waiting lists at referring outpatient clinics and the operating room is studied by [254, 255]. Temporary bed closings may also be unavoidable as a result of staff shortages [165]. In such cases hospitals can act pro-actively, to prevent bed closings during peak demand periods [12].

Methods: computer simulation [112, 116, 165, 255], mathematical programming [12], queueing processes [100, 254].

Admission control. To provide timely access for each different patient group, admission control prescribes the rules according to which various patients with different access time requirements are admitted to nursing wards. At this level, patients are often categorized in elective, urgent and emergency patients. Admission control policies have the objective to match demand and supply such that access times, rejections, surgical care cancellations and misplacements are minimized while bed occupancy is maximized. The challenge is to cope with variability in patient arrivals and length of stay. Smoothing patient inflow, and thus workload at nursing wards, prevents large differences between peak and non-peak periods, and so realizes a more efficient use of resources [112].

Patient resource requirements are another source of variability in the process of admission control. Most references only focus on maximizing utilization of bed resources. This may lead to extreme variations in the utilization of other resources like diagnostic services and nursing care [214]. Also, as with temporarily closing of beds, possible effects of admission control policies on the waiting lists at referring outpatient clinics and the operating room should not be neglected [211]. Admission control policies can be both static (following fixed rules) and dynamic (changing rules responding to the actual situation).

- *Static bed reservation.* To anticipate for the estimated inflow of other patient groups, two types of static bed reservation can be distinguished. The first is refusing admissions of a certain patient type when the bed census exceeds a threshold. For example, to prevent the rejection of emergent admission requests, an inpatient care unit may decide to suspend admissions of elective patients when the number of occupied beds reaches a threshold [82, 93, 133, 165, 168, 195, 211]. As such, a certain number of beds is reserved for emergency patients. This reservation concept is also known as 'earmarking'. Conversely, [136, 227] indicate that earmarking beds for elective postoperative patients can minimize operating room cancellations. In the second static level the number of reserved beds varies, for example per weekday. Examples of such a policy are provided in [18, 230] where for each work day a maximum reservation level for elective patients is determined.
- *Dynamic bed reservation.* Dynamic bed reservation schemes take into account the actual 'state' of a ward, expressed in the bed census per patient type. Together with a prediction of demand, the reservation levels may be determined for a given planning horizon [138] or it may be decided to release reserved beds when demand is low. An example of the latter is found in [136], where bed reservations for elective surgery are released during weekend days.
- *Overflow rules.* In addition to the bed reservation rules, overflow rules prescribe what happens in case all reserved beds for a certain patient type are occupied. In such cases, specific overflow rules prescribe which patient types to place in which units [115]. Generally, patients are reassigned to the correct treatment area as soon as circumstances permit [214]. By allowing overflow and setting appropriate rules, the benefits of bed capacity pooling are utilized (see *capacity dimensioning: care unit size*), while the alignment of patients with their preferred bed types is maximized [165]. Various references focus on predicting the impact of specific overflow rules [118, 115, 165, 208].
- *Influence surgical schedule.* For most inpatient care services the authority on admission control is limited due to the high dependency on the operating room schedule (*see chapter OR*). By

adjusting the surgical schedule, extremely busy and slack periods can be avoided [76, 83, 100, 112, 241] and cancellation of elective surgeries can be avoided [134]. In practice, the operating room planning is generally done under the assumption that a free bed is available for postoperative care [136].

Methods: computer simulation [76, 83, 112, 115, 134, 136, 165, 195, 208, 227], heuristics [241], Markov processes [18, 82, 118, 138], queueing processes [93, 100, 133, 168, 211, 230]
Overleggen hoe laatste beslissing hier te verwerken in afstemming met chapter OR.
Voor conclusies: both for inpatient and OR coordinated planning beneficial, also concluded in [112].

Staff shift scheduling Shifts are hospital duties with a start and end time [31]. Shift scheduling deals with the problem of selecting what shifts are to be worked and how many employees should be assigned to each shift to meet patient demand [81]. For inpatient care services, it generally concerns the specification of 24-hours-a-day-staffing levels divided in a day, evening and night shift, during which demand varies considerably [31, 81]. Typically, this is done for a period of one or two months [188]. Staffing levels need to be set both for each care unit's dedicated nurses and for flexible staff in floating pools [149]. Also, [103] investigates the potential of on-call nurses who are planned to be available during certain shifts and only work when required.

The first step in staff shift scheduling is to determine staffing requirements with a demand model [81, 222], based upon which the bed occupancy levels [214] or sometimes also medical needs are forecasted [149]. The second step is to translate the forecasted demand in workable shifts and in the number of nurses to plan per shift, taken into account the staff resources made available at the strategic decision level [245]. Often, nurse-to-patient ratios are applied in this step [103], which are assumed to imply acceptable levels of patient care and nurse workload [256]. To improve the alignment of care demand and supply, shift scheduling is preferably coordinated with scheduled admissions and surgeries [188], which also helps avoiding high variation in nurse workload pressure [14].

Methods: computer simulation [103], mathematical programming [14, 245, 256], queueing processes [222], *misc.* [149], literature review [31, 81, 188, 214].

Offline operational planning

Admission scheduling. Governing the rules set by tactical admission control policies, on the operational decision level the admission scheduling determines for a specific elective patient the time and date of admission. We think of two reasons for not finding contributions on this decision. First, when admission control policies are thoroughly formulated, admission scheduling is straightforward. Second, as described before, for postoperative inpatient care authority of admission planning is generally at the surgical care services [241].

Methods: -.

Patient to bed assignment. Together with the admission scheduling decision, an elective patient needs to be assigned to a specific bed in a specific ward. Typically, this assignment is carried out a few days before the effective admission of the patient. The objective is to match the patient with a free bed, such that both personal preferences (for example a single or twin room) and medical needs are satisfied [51]. An additional objective may be to balance bed occupancy over different wards.

Methods: heuristics [51], mathematical programming [51].

Discharge planning. Discharge planning is the development of an individualized discharge plan for a patient prior to leaving the hospital. It should ensure that patients are discharged from hospital at an appropriate time in their care and that, with adequate notice, the provision of other care services is timely organized. The aim of discharge planning is to reduce hospital length of stay and unplanned readmission, and improve the coordination of services following discharge from the hospital [209]. As such, discharge planning is highly dependent on availability downstream care services, such as rehabilitation, residential or home care. Therefore, a need is identified for integrated coherent planning across services of different health care organizations [237, 248]. Patients whose medical treatment is complete but cannot leave the hospital are often referred to as 'alternative level of care patients' or 'bed blockers' [236, 248]. Also in discharge planning it is worthwhile to anticipate for seasonality effects. In [237] the so-called winter bed crisis is mentioned, a phenomenon appearing in British hospitals in the period two or three weeks after Christmas. Each year, a bed shortage occurs, as a result of increased demand due to bad weather and influenza and blocked discharges due to a lack of social services.

Methods: computer simulation [237], queueing processes [248].

Staff to shift assignment Staff to shift assignment deals with the allocation of staff members to shifts over a period of several weeks [81]. The term 'nurse rostering' is also often used for this step in inpatient care services personnel planning [31]. The objective is to meet the required shift staffing levels set on the tactical level, while satisfying a complex set of restrictions involving work regulations and employee preferences [31]. Night and weekend shifts, days off and leaves have to be distributed fairly [188, 214, 256] and as much as possible according to individual preferences [81]. In most cases, to compose a roster for each individual, first sensible combinations or patterns of shifts are generated (cyclic or non-cyclic), called 'lines-of-work', after which individuals are assigned to these lines-of-work [81]. Sometimes, staff to shift assignment is integrated with staff shift scheduling [31, 256].

Methods: mathematical programming [256], literature review [31, 81, 188, 214].

Online operational planning

Elective admission rescheduling. Based on the current patient status and status of the inpatient care facility, it has to be decided whether a scheduled admission can proceed as planned. Circumstances may call for postponing or cancelling the admission, to reschedule it to another care unit, or to change the bed assignment. Various factors will be taken into consideration such as severity of illness, age, expected length of stay, the probable treatment outcome and (estimated) bed availability, conditions of other patients (in view of the possibility of predischarging an other patient) [157, 135, 210]. This decision is generally made on the planned day of admission or a few days in advance. In the latter case this can be considered on offline decision. Rescheduling admissions can have a major impact on the operations at the surgical theatre [135].

Methods: computer simulation [135], queueing processes [135, 210], *misc.* [157].

Acute admission handling. For an acute admission request it has to be be decided whether to admit the emergency patient and if so to which care unit, which bed, and on what notice. The tactical admission control rules act as guideline. As with rescheduling elective admissions, the status of both the patient and the inpatient care facility are taken into account [135, 210]. In [135] it is calculated how long the waiting will be if the patient is placed on 'the admission list' and[210] proposes and evaluates an admission policy to maximize the expected incremental number of lives saved from selecting the best patients for admission to an Intensive Care Unit.

Methods: computer simulation [135], queueing processes [135, 210].

Staff rescheduling. At the start of a shift, the staff schedule is reconsidered. Based on severity of need in each care unit, the float nurses and other flexible employees are assigned to a specific unit and a reassignment of dedicated nurses may also take place [31, 214]. In addition, before and during the shift, the staff capacities among units may be adjusted to unpredicted demand fluctuations and staff absenteeism by using float, part-time, on-call nurses overtime, and voluntary absenteeism [103, 188].

Methods: computer simulation [103], mathematical programming [192], literature review [31, 188, 214].

Nurse to patient assignment. At the beginning of each shift nurses are assigned to take care for a group of patients. This assignment is done with the objective to provide each patient with an appropriate level of care and to balance work loads [173, 217]. Distributing work fairly among nurses improves the quality of care [173]. Generally, the assignment has to satisfy specified nurse-to-patient ratios [192]. Additionally, when patient conditions within one care unit can differ considerably, for each specific patient an estimate of the severity of the condition (and thereby expected workload) is made, in most cases on the basis of a certain severity scoring system [173]. In [192] it is explicitly taken into account that patient conditions can vary during a shift and therefore care needs. Preferably, at the beginning of each shift it is also already decided to which nurse unanticipated patient will be assigned [192].

Methods: computer simulation [217], heuristics [173], mathematical programming [173, 192].

Transfer scheduling. Continuously, the transfer scheduling is done of inpatients to the appropriate care units within the hospital for treatment or diagnoses throughout their stay [188]. This also includes transportation planning. We have not found OR/MS contributions on this topic.

Methods:-.

References

[1] E. Aarts and J. Lenstra. *Local search in combinatorial optimization*. Princeton University Press, 2003.

[2] W. Abernathy and J. Hershey. A spatial-allocation model for regional health-services planning. *Operations Research*, 20(3):629–642, 1972.

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

[4] L. Aiken, S. Clarke, D. Sloane, J. Sochalski, and J. Silber. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *Jama*, 288(16):1987–1993, 2002.

[5] E. Akcali, M. Coté, and C. Lin. A network flow approach to optimizing hospital bed capacity decisions. *Health Care Management Science*, 9(4):391–404, 2006.

[6] R. Akkerman and M. Knip. Reallocation of beds to reduce waiting time for cardiac surgery. *Health Care Management Science*, 7(2):119–126, 2004.

[7] R. Anthony. *Planning and control systems: a framework for analysis*. Division of Research, Graduate School of Business Administration, Harvard University, 1965.

[8] J. Arnaout. Heuristics for the Maximization of Operating Rooms Utilization Using Simulation. *Simulation*, 86(8-9):573, 2010.

[9] R. Ashton, L. Hague, M. Brandreth, D. Worthington, and S. Cropper. A simulation-based study of a NHS Walk-in Centre. *Journal of the Operational Research Society*, 56(2):153–161, 2005.

[10] V. Augusto, X. Xie, and V. Perdomo. Operating theatre scheduling with patient recovery in both operating rooms and recovery beds. *Computers & Industrial Engineering*, 58(2):231–238, 2010.

[11] M. Babes and G. Sarma. Out-patient queues at the Ibn-Rochd health centre. *Journal of the Operational Research Society*, 42(10):845–855, 1991.

[12] R. Beech, R. Brough, and B. Fitzsimons. The development of a decision-support system for planning services within hospitals. *The Journal of the Operational Research Society*, 41(11):995–1006, 1990.

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

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

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

[16] J. Bennett and D. Worthington. An example of a good but partially successful OR engagement: Improving outpatient clinic operations. *Interfaces*, pages 56–69, 1998.

[17] J. Bertrand, J. Wortmann, and J. Wijngaard. *Production control: a structural and design oriented approach*. Elsevier Science Inc. New York, NY, USA, 1990.

[18] J. Bithell. A class of discrete-time models for the study of hospital admission systems. *Operations Research*, 17(1):48–69, 1969.

[19] E. Blair Charles and L. Eric. A queueing network approach to health care planning with an application to burn care in New York state. *Socio-economic Planning Sciences*, 15(5):207–216, 1981.

[20] J. Blake and M. Carter. Surgical process scheduling: a structured review. *Journal of the Society for Health Systems*, 5(3):17–30, 1997.

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

[22] J. Blake, F. Dexter, and J. Donald. Operating Room Managers' Use of Integer Programming for Assigning Block Time to Surgical Groups: A Case Study. *Anesthesia & Analgesia*, 94(1):143–148, 2002.

[23] J. Blake and J. Donald. Mount Sinai hospital uses integer programming to allocate operating room time. *Interfaces*, 32(2):63–73, 2002.

[24] J. Bowers and G. Mould. Concentration and the variability of orthopaedic demand. *Journal of the Operational Research Society*, 53(2):203–210, 2002.

[25] J. Bowers and G. Mould. Managing uncertainty in orthopaedic trauma theatres. *European Journal of Operational Research*, 154(3):599–608, 2004.

[26] M. Brahimi and D. Worthington. Queueing Models for Out-Patient Appointment Systems–A Case Study. *Journal of the Operational Research Society*, 42(9):733–746, 1991.

[27] S. Brailsford, P. Harper, B. Patel, and M. Pitt. An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation*, 3(3):130–140, 2009.

[28] S. Brailsford and J. Vissers. Or in healthcare: A european perspective. *European Journal of Operational Research*, 212(2):223 – 234, 2011.

[29] M. Brandeau, F. Sainfort, and W. Pierskalla, editors. *Operations Research and Health Care: a Handbook of Methods and Applications*. International Series in Operations Research & Management Science, Vol. 70. Kluwer Academic Publishers, 2004.

[30] J. Brunner, J. Bard, and R. Kolisch. Midterm scheduling of physicians with flexible shifts using branch and price. *IIE Transactions*, 43(2):84–109, 2011.

[31] E. Burke, P. De Causmaecker, G. Berghe, and H. Van Landeghem. The state of the art of nurse rostering. *Journal of scheduling*, 7(6):441–499, 2004.

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

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

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

[35] T. Cayirli and E. Veral. Outpatient scheduling in health care: a review of literature. *Production and Operations Management*, 12(4):519–549, 2003.

[36] T. Cayirli, E. Veral, and R. H. Designing appointment scheduling systems for ambulatory care services. *Health Care Management Science*, 9:47–58, 2006.

[37] E. Cerdá, L. Pablos, and M. Rodriguez. Waiting lists for surgery. *Patient Flow: Reducing Delay in Healthcare Delivery*, pages 151–187, 2006.

[38] S. Chaabane, N. Meskens, A. Guinet, and M. Laurent. Comparison of two methods of operating theatre planning: Application in Belgian Hospital. *Journal of Systems Science and Systems Engineering*, 17(2):171–186, 2008.

[39] S. Chand, H. Moskowitz, J. B. Norris, S. Shade, and D. R. Willis. Improving patient flow at an outpatient clinic: study of sources of variability and improvement factors. *Health Care Manag Sci*, 12(3):325–340, 2009.

[40] B. Cheang, H. Li, A. Lim, and B. Rodrigues. Nurse rostering problems–a bibliographic survey. *European Journal of Operational Research*, 151(3):447–460, 2003.

[41] C. Chien, F. Tseng, and C. Chen. An evolutionary approach to rehabilitation patient scheduling: A case study. *European Journal of Operational Research*, 189(3):1234–1253, 2008.

[42] J. Cochran and A. Bharti. Stochastic bed balancing of an obstetrics hospital. *Health care management science*, 9(1):31–45, 2006.

[43] T. Coelli, D. Prasada Rao, and G. Battese. *An introduction to efficiency and productivity analysis*. Kluwer Academic Publishers, 2005.

[44] M. Cohen, J. Hershey, and E. Weiss. Analysis of capacity decisions for progressive patient care hospital facilities. *Health Services Research*, 15(2):145, 1980.

[45] D. Conforti, F. Guerriero, and R. Guido. Optimization models for radiotherapy patient scheduling. *4OR: A Quarterly Journal of Operations Research*, 6(3):263–278, 2008.

[46] D. Conforti, F. Guerriero, and R. Guido. Non-block scheduling with priority for radiotherapy treatments. *European Journal of Operational Research*, 201(1):289–296, 2010.

[47] A. Costa, S. Ridley, A. Shahani, P. Harper, V. De Senna, and M. Nielsen. Mathematical modelling and simulation for planning critical care capacity*. *Anaesthesia*, 58(4):320–327, 2003.

[48] S. Creemers and M. Lambrecht. An advanced queueing model to analyze appointment-driven service systems. *Computers & Operations Research*, 36(10):2773–2785, 2009.

[49] R. W. Day, M. D. Dean, R. Garfinkel, and S. Thompson. Improving patient flow in a hospital through dynamic allocation of cardiac diagnostic testing time slots. *Decision Support Systems*, 49(4):463 – 473, 2010.

[50] A. de Bruin, A. van Rossum, M. Visser, and G. Koole. Modeling the emergency cardiac in-patient flow: an application of queuing theory. *Health Care Management Science*, 10(2):125–137, 2007.

[51] P. Demeester, W. Souffriau, P. D. Causmaecker, and G. V. Berghe. A hybrid tabu search algorithm for automatically assigning patients to beds. *Artificial Intelligence in Medicine*, 48(1):61 – 70, 2010.

[52] B. Denton and D. Gupta. A sequential bounding approach for optimal appointment scheduling. *IIE Transactions*, 35(11):1003–1016, 2003.

[53] B. Denton, A. Miller, H. Balasubramanian, and T. Huschka. Optimal allocation of surgery blocks to operating rooms under uncertainty. *Operations research*, 58(4-Part-1):802–816, 2010.

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

[55] F. Dexter. Design of appointment systems for preanesthesia evaluation clinics to minimize patient waiting times: a review of computer simulation and patient survey studies. *Anesthesia & Analgesia*, 89(4):925, 1999.

[56] F. Dexter. A strategy to decide whether to move the last case of the day in an operating room to another empty operating room to decrease overtime labor costs. *Anesthesia & Analgesia*, 91(4):925, 2000.

[57] F. Dexter. Bibliography of operating room management articles. *Retrieved January 25, 2010, from: http://www.franklindexter.com/*, 2010.

[58] F. Dexter, R. Epstein, and H. Marsh. A statistical analysis of weekday operating room anesthesia group staffing costs at nine independently managed surgical suites. *Anesthesia & Analgesia*, 92(6):1493–1498, 2001.

[59] F. Dexter and J. Ledolter. Bayesian prediction bounds and comparisons of operating room times even for procedures with few or no historic data. *Anesthesiology*, 103(6):1259–1267, 2005.

[60] F. Dexter, J. Ledolter, and R. Wachtel. Tactical decision making for selective expansion of operating room resources incorporating financial criteria and uncertainty in subspecialties' future workloads. *Anesthesia & Analgesia*, 100(5):1425–1432, 2005.

[61] F. Dexter and A. Macario. Decrease in case duration required to complete an additional case during regularly scheduled hours in an operating room suite: a computer simulation study. *Anesthesia & Analgesia*, 88(1):72–76, 1999.

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

[63] F. Dexter, A. Macario, and L. ONeill. A strategy for deciding operating room assignments for second-shift anesthetists. *Anesthesia & Analgesia*, 89(4):920–924, 1999.

[64] F. Dexter, A. Macario, and L. ONeill. Scheduling surgical cases into overflow block time–Computer simulation of the effects of scheduling strategies on operating room labor costs. *Anesthesia & Analgesia*, 90(4):980–988, 2000.

[65] F. Dexter, A. Macario, and R. Traub. Optimal sequencing of urgent surgical cases. *Journal of Clinical Monitoring and Computing*, 15(3):153–162, 1999.

[66] F. Dexter, A. Macario, and R. Traub. Which algorithm for scheduling add-on elective cases maximizes operating room utilization?: Use of bin packing algorithms and fuzzy constraints in operating room management. *Anesthesiology*, 91(5):1491–1500, 1999.

[67] F. Dexter, A. Macario, R. Traub, M. Hopwood, and D. Lubarsky. An operating room scheduling strategy to maximize the use of operating room block time: computer simulation of patient scheduling and survey of patients preferences for surgical waiting time. *Anesthesia & Analgesia*, 89(1):7–20, 1999.

[68] F. Dexter, A. Macario, R. Traub, and D. Lubarsky. Operating room utilization alone is not an accurate metric for the allocation of operating room block time to individual surgeons with low caseloads. *Anesthesiology*, 98(5):1243, 2003.

[69] F. Dexter and R. Traub. Statistical method for predicting when patients should be ready on the day of surgery. *Anesthesiology*, 93(4):1107, 2000.

[70] F. Dexter and R. Traub. How to schedule elective surgical cases into specific operating rooms to maximize the efficiency of use of operating room time. *Anesthesia & Analgesia*, 94(4):933–942, 2002.

[71] F. Dexter, R. Traub, and P. Lebowitz. Scheduling a delay between different surgeons' cases in the same operating room on the same day using upper prediction bounds for case durations. *Anesthesia & Analgesia*, 92(4):943–946, 2001.

[72] F. Dexter, R. Traub, and A. Macario. How to release allocated operating room time to increase efficiency: predicting which surgical service will have the most underutilized operating room time. *Anesthesia & Analgesia*, 96(2):507–512, 2003.

[73] F. Dexter, R. Wachtel, R. Epstein, J. Ledolter, and M. Todd. Analysis of Operating Room Allocations to Optimize Scheduling of Specialty Rotations for Anesthesia Trainees. *Anesthesia & Analgesia*, 111(2):520, 2010.

[74] F. Dexter, R. E. Wachtel, M. Sohn, J. Ledolter, E. U. Dexter, and A. Macario. Quantifying Effect of a Hospitals Caseload for a Surgical Specialty on That of Another Hospital Using Multi-Attribute Market Segments. *Health Care Management Science*, 8:121–131, 2005.

[75] V. F. Dokmeci. Planning ambulatory health care delivery systems. *Omega*, 4(5):617 – 622, 1976.

[76] M. Dumas. Simulation modeling for hospital bed planning. *Simulation*, 43(2):69, 1984.

[77] M. Dumas. Hospital bed utilization: an implemented simulation approach to adjusting and maintaining appropriate levels. *Health services research*, 20(1):43, 1985.

[78] EBSCOhost. *Retrieved August 10, 2010, from: http://www.ebscohost.com/*, 2010.

[79] G. Edward, S. Das, S. Elkhuizen, P. Bakker, J. Hontelez, M. Hollmann, B. Preckel, and L. Lemaire. Simulation to analyse planning difficulties at the preoperative assessment clinic. *British Journal of Anaesthesia*, 100(2):195, 2008.

[80] S. Elkhuizen, S. Das, P. Bakker, and J. Hontelez. Using computer simulation to reduce access time for outpatient departments. *British Medical Journal*, 16(5):382, 2007.

[81] A. Ernst, H. Jiang, M. Krishnamoorthy, and D. Sier. Staff scheduling and rostering: A review of applications, methods and models. *European journal of operational research*, 153(1):3–27, 2004.

[82] A. Esogbue and A. Singh. A stochastic model for an optimal priority bed distribution problem in a hospital ward. *Operations Research*, 24(5):884–898, 1976.

[83] J. Everett. A decision support simulation model for the management of an elective surgery waiting system. *Health Care Management Science*, 5(2):89–95, 2002.

[84] H. E.W., M. van Houdenhoven, and P. Hulshof. A framework for health care planning and control. *Working paper*, University of Twente, 2010.

[85] H. Fei, C. Chu, and N. Meskens. Solving a tactical operating room planning problem by a column-generation-based heuristic procedure with four criteria. *Annals of Operations Research*, 166(1):91–108, 2009.

[86] H. Fei, C. Chu, N. Meskens, and A. Artiba. Solving surgical cases assignment problem by a branch-and-price approach. *International Journal of Production Economics*, 112(1):96–108, 2008.

[87] H. Fei, N. Meskens, and C. Chu. A planning and scheduling problem for an operating theatre using an open scheduling strategy. *Computers & Industrial Engineering*, 58(2):221–230, 2010.

[88] R. Fetter and J. Thompson. The simulation of hospital systems. *Operations Research*, pages 689–711, 1965.

[89] R. Fetter and J. Thompson. Patients' waiting time and doctors' idle time in the outpatient setting. *Health Services Research*, 1(1):66, 1966.

[90] D. Fone, S. Hollinghurst, M. Temple, A. Round, N. Lester, A. Weightman, K. Roberts, E. Coyle, G. Bevan, and S. Palmer. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health*, 25(4):325, 2003.

[91] B. Fries. Bibliography of operations research in health-care systems. *Operations Research*, pages 801–814, 1976.

[92] B. Fries and V. Marathe. Determination of optimal variable-sized multiple-block appointment systems. *Operations Research*, 29(2):324–345, 1981.

[93] S. Gallivan, M. Utley, T. Treasure, and O. Valencia. Booked inpatient admissions and hospital capacity: mathematical modelling study. *BMJ*, 324(7332):280, 2002.

[94] S. Ganguli, J. Tham, and B. d'Othee. Establishing an outpatient clinic for minimally invasive vein care. *American Journal of Roentgenology*, 188(6):1506, 2007.

[95] Y. Gerchak, D. Gupta, and M. Henig. Reservation planning for elective surgery under uncertain demand for emergency surgery. *Management Science*, pages 321–334, 1996.

[96] A. Gnanlet and W. Gilland. Sequential and simultaneous decision making for optimizing health care resource flexibilities. *Decision Sciences*, 40(2):295–326, 2009.

[97] J. Goldman, H. Knappenberger, and J. Eller. Evaluating bed allocation policy with computer simulation. *Health Services Research*, 3(2):119, 1968.

[98] F. Gorunescu, S. McClean, and P. Millard. A queueing model for bed-occupancy management and planning of hospitals. *Journal of the Operational Research Society*, 53(1):19–24, 2002.

[99] L. Green. Queueing analysis in healthcare. *Patient flow: reducing delay in healthcare delivery*, pages 281–307, 2006.

[100] L. Green and V. Nguyen. Strategies for cutting hospital beds: the impact on patient service. *Health Services Research*, 36(2):421–442, 2001.

[101] L. Green and S. Savin. Reducing delays for medical appointments: A queueing approach. *Operations Research*, 56(6):1526–1538, 2008.

[102] L. Green, S. Savin, and B. Wang. Managing patient service in a diagnostic medical facility. *Operations Research*, 54(1):11–25, 2006.

[103] J. Griffiths, N. Price-Lloyd, M. Smithies, and J. Williams. Modelling the requirement for supplementary nurses in an intensive care unit. *Journal of the Operational Research Society*, 56(2):126–133, 2005.

[104] F. Guerriero and R. Guido. Operational research in the management of the operating theatre: a survey. *Health care management science*, pages 1–26, 2010.

[105] A. Guinet and S. Chaabane. Operating theatre planning. *International Journal of Production Economics*, 85(1):69–81, 2003.

[106] E. Güneş. Modeling time allocation for prevention in primary care. *Central European Journal of Operations Research*, 17(3):359–380, 2009.

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

[108] D. Gupta and B. Denton. Appointment scheduling in health care: Challenges and opportunities. *IIE Transactions*, 40(9):800–819, 2008.

[109] D. Gupta and L. Wang. Revenue management for a primary-care clinic in the presence of patient choice. *Operations Research-Baltimore*, 56(3):576–592, 2008.

[110] R. W. Hall, editor. *Patient Flow: Reducing Delay in Healthcare Delivery*. International Series in Operations Research & Management Science, Vol. 91. Springer, 2006.

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

[112] P. Harper. A framework for operational modelling of hospital resources. *Health care management science*, 5(3):165–173, 2002.

[113] P. Harper and H. Gamlin. Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach. *OR Spectrum*, 25(2):207–222, 2003.

[114] P. Harper and A. Shahani. Modelling for the planning and management of bed capacities in hospitals. *The Journal of the Operational Research Society*, 53(1):11–18, 2002.

[115] P. Harper, A. Shahani, J. Gallagher, and C. Bowie. Planning health services with explicit geographical considerations: a stochastic location-allocation approach. *Omega*, 33(2):141–152, 2005.

[116] R. Harris. Hospital bed requirements planning. *European Journal of Operational Research*, 25(1):121–126, 1986.

[117] G. Harrison, A. Shafer, and M. Mackay. Modelling variability in hospital bed occupancy. *Health Care Management Science*, 8(4):325–334, 2005.

[118] J. Hershey, E. Weiss, and M. Cohen. A stochastic service network model with application to hospital facilities. *Operations Research*, 29(1):1–22, 1981.

[119] F. Hillier. *Introduction to operations research*. McGraw-Hill Science/Engineering/Math; 9 edition, 2009.

[120] C. Ho and H. Lau. Minimizing total cost in scheduling outpatient appointments. *Management Science*, 38(12):1750–1764, 1992.

[121] C. Ho and H. Lau. Evaluating the impact of operating conditions on the performance of appointment scheduling rules in service systems. *European Journal of Operational Research*, 112(3):542–553, 1999.

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

[123] X. HUANG. A planning model for requirement of emergency beds. *Mathematical Medicine and Biology*, 12(3-4):345, 1995.

[124] X. Huang. Decision making support in reshaping hospital medical services. *Health care management science*, 1(2):165–173, 1998.

[125] W. Hughes and S. Soliman. Short-term case mix management with linear programming. *Hospital & health services administration*, 30(1):52–60.

[126] INFORMS Website. *Retrieved January 25, 2010, from: http://www.informs.org/*, 2011.

[127] E. Jack and T. Powers. A review and synthesis of demand management, capacity management and performance in health-care services. *International Journal of Management Reviews*, 11(2):149–174, 2009.

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

[129] P. Joustra, J. de Wit, V. Struben, B. Overbeek, P. Fockens, and S. Elkhuizen. Reducing access times for an endoscopy department by an iterative combination of computer simulation and Linear Programming. *Health care management science*, 13(1):17–26, 2010.

[130] J. Jun, S. Jacobson, and J. Swisher. Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, 50(2):109–123, 1999.

[131] G. Kaandorp and G. Koole. Optimal outpatient appointment scheduling. *Health Care Management Science*, 10(3):217–229, 2007.

[132] E. Kao and G. Tung. Bed allocation in a public health care delivery system. *Management Science*, 27(5):507, 1981.

[133] A. Kapadia and Y. Fasihullah. Finite capacity priority queues with potential health applications. *Computers & Operations Research*, 12(4):411–420, 1985.

[134] S. Kim and I. Horowitz. Scheduling hospital services: the efficacy of elective-surgery quotas. *Omega*, 30(5):335–346, 2002.

[135] S. Kim, I. Horowitz, K. Young, and T. Buckley. Analysis of capacity management of the intensive care unit in a hospital. *European Journal of Operational Research*, 115(1):36–46, 1999.

[136] S. Kim, I. Horowitz, K. Young, and T. Buckley. Flexible bed allocation and performance in the intensive care unit. *Journal of Operations Management*, 18(4):427–443, 2000.

[137] A. Kokangul. A combination of deterministic and stochastic approaches to optimize bed capacity in a hospital unit. *Computer methods and programs in biomedicine*, 90(1):56–65, 2008.

[138] P. Kolesar. A Markovian model for hospital admission scheduling. *Management Science*, 16(6):384–396, 1970.

[139] R. Kolisch and S. Sickinger. Providing radiology health care services to stochastic demand of different customer classes. *OR Spectrum*, 30(2):375–395, 2008.

[140] J. Kros, S. Dellana, and D. West. Overbooking Increases Patient Access at East Carolina University's Student Health Services Clinic. *Interfaces*, 39(3):271, 2009.

[141] P. Kuzdrall, N. Kwak, and H. Schmitz. Simulating space requirements and scheduling policies in a hospital surgical suite. *Simulation*, 36(5):163, 1981.

[142] N. Kwak, P. Kuzdrall, and H. Schmitz. Simulating the use of space in a hospital surgical suite. *Simulation*, 25(5):147, 1975.

[143] N. Kwak, P. Kuzdrall, and H. Schmitz. The GPSS simulation of scheduling policies for surgical patients. *Management Science*, 22(9):982–989, 1976.

[144] L. LaGanga and S. Lawrence. Clinic Overbooking to Improve Patient Access and Increase Provider Productivity*. *Decision Sciences*, 38(2):251–276, 2007.

[145] M. Lagergren. What is the role and contribution of models to management and research in the health services? A view from Europe. *European Journal of Operational Research*, 105(2):257–266, 1998.

[146] M. Lamiri, F. Grimaud, and X. Xie. Optimization methods for a stochastic surgery planning problem. *International Journal of Production Economics*, 120(2):400–410, 2009.

[147] M. Lamiri, X. Xie, A. Dolgui, and F. Grimaud. A stochastic model for operating room planning with elective and emergency demand for surgery. *European Journal of Operational Research*, 185(3):1026–1037, 2008.

[148] M. Lamiri, X. Xie, and S. Zhang. Column generation approach to operating theater planning with elective and emergency patients. *IIE Transactions*, 40(9):838–852, 2008.

[149] T. Landau, T. Thiagarajan, and R. Ledley. Cost containment in the concentrated care center: a study of nursing, bed and patient assignment policies. *Computers in Biology and Medicine*, 13(3):205–238, 1983.

[150] J. R. Langabeer II. *Health Care Operations Management: A Quantitative Approach to Business and Logistics*. Jones & Bartlett Publishers, 2007.

[151] M. Lavieri and M. Puterman. Optimizing nursing human resource planning in British Columbia. *Health care management science*, 12(2):119–128, 2009.

[152] A. Law. *Simulation Modeling and Analysis*. McGraw-Hill Publishing Co., 4th edition edition, 2006.

[153] D. Lee and S. Zenios. Optimal Capacity Overbooking for the Regular Treatment of Chronic Conditions. *Operations research*, 57(4):852–865, 2009.

[154] B. Lehaney, S. Clarke, and R. Paul. A case of an intervention in an outpatients department. *Journal of the Operational Research Society*, 50(9):877–891, 1999.

[155] L. Li and W. Benton. Performance measurement criteria in health care organizations: Review and future research directions* 1. *European Journal of Operational Research*, 93(3):449–468, 1996.

[156] C. Liao, C. Pegden, and M. Rosenshine. Planning timely arrivals to a stochastic production or service system. *IIE transactions*, 25(5):63–73, 1993.

[157] S. Littig and M. Isken. Short term hospital occupancy prediction. *Health Care Management Science*, 10(1):47–66, 2007.

[158] L. Liu and X. Liu. Block appointment systems for outpatient clinics with multiple doctors. *Journal of the Operational Research Society*, 49(12):1254–1259, 1998.

[159] W. Lovejoy and Y. Li. Hospital operating room capacity expansion. *Management Science*, 48(11):1369–1387, 2002.

[160] M. Mackay. Practical experience with bed occupancy management and planning systems: an Australian view. *Health Care Management Science*, 4(1):47–56, 2001.

[161] J. Magerlein and J. Martin. Surgical demand scheduling: a review. *Health Services Research*, 13(4):418–433, 1978.

[162] E. Marcon and F. Dexter. Impact of surgical sequencing on post anesthesia care unit staffing. *Health Care Management Science*, 9(1):87–98, 2006.

[163] E. Marcon, S. Kharraja, and G. Simonnet. The operating theatre planning by the follow-up of the risk of no realization. *International Journal of Production Economics*, 85(1):83–90, 2003.

[164] R. Marjamaa, P. Torkki, E. Hirvensalo, and O. Kirvel
"a. What is the best workflow for an operating room? A simulation study of five scenarios. *Health Care Management Science*, 12(2):142–146, 2009.

[165] B. Masterson, T. Mihara, G. Miller, S. Randolph, M. Forkner, and A. Crouter. Using models and data to support optimization of the military health system: A case study in an intensive care unit. *Health Care Management Science*, 7(3):217–224, 2004.

[166] M. Matta and S. Patterson. Evaluating multiple performance measures across several dimensions at a multi-facility outpatient center. *Health Care Management Science*, 10(2):173–194, 2007.

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

[168] J. McClain. A model for regional obstetric bed planning. *Health Services Research*, 13(4):378–394, 1978.

[169] D. McLaughlin and J. Hays. *Healthcare Operations Management*, volume 7.

[170] Medical Subject Headings (MeSH). *Retrieved January 25, 2010, from: http://www.nlm.nih.gov/mesh/*, 2010.

[171] D. Min and Y. Yih. An elective surgery scheduling problem considering patient priority. *Computers & Operations Research*, 37(6):1091–1099, 2010.

[172] D. Min and Y. Yih. Scheduling elective surgery under uncertainty and downstream capacity constraints. *European Journal of Operational Research*, 206(3):642–652, 2010.

[173] C. Mullinax and M. Lawley. Assigning patients to nurses in neonatal intensive care. *The Journal of the Operational Research Society*, 53(1):25–35, 2002.

[174] K. Muthuraman and M. Lawley. A stochastic overbooking model for outpatient clinical scheduling with no-shows. *IIE Transactions*, 40(9):820–837, 2008.

[175] NBII. Website of the National Biological Information Infrastructure (NBII). *Retrieved October 10, 2010, from: http://www.nbii.gov*, 2010.

[176] J. Nguyen, P. Six, D. Antonioli, P. Glemain, G. Potel, P. Lombrail, and P. Le Beux. A simple method to optimize hospital beds capacity. *International Journal of Medical Informatics*, 74(1):39–49, 2005.

[177] J. Nguyen, P. Six, T. Chaussalet, D. Antonioli, P. Lombrail, and P. Le Beux. An Objective Method for Bed Capacity Planning in a Hospital Department-A Comparison with Target Ratio Methods. *Methods of Information in Medicine*, 46(4):399–405, 2007.

[178] J. Nguyen, P. Six, R. Parisot, D. Antonioli, F. Nicolas, and P. Lombrail. A universal method for determining intensive care unit bed requirements. *Intensive care medicine*, 29(5):849–852, 2003.

[179] M. Olivares, C. Terwiesch, and L. Cassorla. Structural estimation of the newsvendor model: an application to reserving operating room time. *Manage Sci*, 54(1):41–55, 2008.

[180] ORchestra. Developed by Centre for Healthcare Operations and Improvement Research (CHOIR) at the University of Twente. *Retrieved August 10, 2010, from: http://www.utwente.nl/choir/en/orchestra/*, 2010.

[181] ORCHID. Developed by Centre for Research in Healthcare Engineering (CRHE) at the University of Toronto. *Retrieved August 10, 2010, accessible through: http://www.utwente.nl/choir/en/orchestra/*, 2010.

[182] Organisation of Economic Co-operation and Development (OECD). *Data retrieved October 10, 2010, from: http://www.oecd.org/health*, 2010.

[183] Y. Ozcan. *Quantitative Methods in Health Care Management: Techniques and Applications*. Jossey Bass/Wiley, 2nd edition edition, 2009.

[184] C. Papadimitriou and K. Steiglitz. *Combinatorial optimization: algorithms and complexity*. Dover Pubns, 1998.

[185] J. Patrick, M. Puterman, and M. Queyranne. Dynamic multi-priority patient scheduling for a diagnostic resource. *Operations Research*, 56(6):1507–1525, 2008.

[186] M. Persson and J. Persson. Analysing management policies for operating room planning using simulation. *Health care management science*, 13(2):182–191, 2010.

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

[188] W. Pierskalla and D. Brailer. Applications of operations research in health care delivery. *Operations research and the public sector*, pages 469–505, 1994.

[189] M. Porter. *Competitive advantage*, volume 15. Free Press New York, 1985.

[190] Z. Przasnyski. Operating room scheduling. A literature review. *AORN journal*, 44(1):67, 1986.

[191] PubMed. *Retrieved August 10, 2010, from: http://www.pubmed.gov/*, 2010.

[192] P. Punnakitikashem, J. Rosenberger, and D. Buckley Behan. Stochastic programming for nurse assignment. *Computational Optimization and Applications*, 40(3):321–349, 2008.

[193] X. Qu, R. Rardin, J. Williams, and D. Willis. Matching daily healthcare provider capacity to demand in advanced access scheduling systems. *European Journal of Operational Research*, 183(2):812–826, 2007.

[194] T. Reilly, V. Marathe, and B. Fries. A delay-scheduling model for patients using a walk-in clinic. *Journal of medical systems*, 2(4):303–313, 1978.

[195] J. Ridge, S. Jones, M. Nielsen, and A. Shahani. Capacity planning for intensive care units. *European journal of operational research*, 105(2):346–355, 1998.

[196] E. Rising, R. Baron, and B. Averill. A systems analysis of a university-health-service outpatient clinic. *Operations Research*, 21(5):1030–1047, 1973.

[197] L. Robinson and R. Chen. Scheduling doctors' appointments: optimal and empirically-based heuristic policies. *IIE Transactions*, 35(3):295–307, 2003.

[198] L. W. Robinson and R. R. Chen. A Comparison of Traditional and Open-Access Policies for Appointment Scheduling. *MANUFACTURING SERVICE OPERATIONS MANAGEMENT*, 12(2):330–346, 2010.

[199] T. Rohleder, D. Bischak, and L. Baskin. Modeling patient service centers with simulation and system dynamics. *Health Care Management Science*, 10(1):1–12, 2007.

[200] B. Roland, C. Di Martinelly, F. Riane, and Y. Pochet. Scheduling an operating theatre under human resource constraints. *Computers & Industrial Engineering*, 58(2):212–220, 2010.

[201] S. M. Ross. *Introduction to probability models*. Academic Press, 9 edition, 2007.

[202] R. Ruth. A mixed integer programming model for regional planning of a hospital inpatient service. *Management Science*, pages 521–533, 1981.

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

[204] H. Schmitz and N. Kwak. Monte Carlo simulation of operating-room and recovery-room usage. *Operations Research*, 20(6):1171–1180, 1972.

[205] H. H. Schmitz, N. K. Kwak, and P. J. Kuzdrall. Determination of surgical suite capacity and an evaluation of patient scheduling policies. *RAIRO-Recherche Operationelle-Operations Research*, 12(1):3–14, 1978.

[206] A. Schrijver. *Combinatorial optimization: polyhedra and efficiency*. Springer Verlag, 2003.

[207] Scopus. *Retrieved August 10, 2010, from: http://www.scopus.com/*, 2010.

[208] A. Shahani, S. Ridley, and M. Nielsen. Modelling patient flows as an aid to decision making for critical care capacities and organisation. *Anaesthesia*, 63(10):1074–1080, 2008.

[209] S. Shepperd, J. Parkes, J. McClaren, and C. Phillips. Discharge planning from hospital to home. *Cochrane database of systematic reviews (Online)*, (1):CD000313, 2004.

[210] A. Shmueli, C. Sprung, and E. Kaplan. Optimizing admissions to an intensive care unit. *Health Care Management Science*, 6(3):131–136, 2003.

[211] W. Shonick and J. Jackson. An improved stochastic model for occupancy-related random variables in general-acute hospitals. *Operations Research*, 21(4):952–965, 1973.

[212] D. Sier, P. Tobin, and C. McGurk. Scheduling surgical procedures. *Journal of the Operational Research Society*, 48(9):884–891, 1997.

[213] K. Smith, A. Over Jr, M. Hansen, F. Golladay, and E. Davenport. Analytic framework and measurement strategy for investigating optimal staffing in medical practice. *Operations Research*, pages 815–841, 1976.

[214] V. Smith-Daniels, S. Schweikhart, and D. Smith-Daniels. Capacity Management in Health Care Services: Review and Future Research Directions*. *Decision Sciences*, 19(4):889–919, 1988.

[215] A. Sonnenberg. How to overbook procedures in the endoscopy unit. *Gastrointestinal endoscopy*, 69(3S):710–715, 2009.

[216] E. Stafford Jr and S. Aggarwal. Managerial analysis and decision-making in outpatient health clinics. *Journal of the Operational Research Society*, 30(10):905–915, 1979.

[217] D. Sundaramoorthi, V. Chen, J. Rosenberger, S. Kim, and D. Buckley-Behan. A data-integrated simulation model to evaluate nurse–patient assignments. *Health care management science*, 12(3):252–268, 2009.

[218] J. Swisher, S. Jacobson, J. Jun, and O. Balci. Modeling and analyzing a physician clinic environment using discrete-event (visual) simulation. *Computers and Operations Research*, 28(2):105–125, 2001.

[219] J. R. Swisher and S. H. Jacobson. Evaluating the design of a family practice healthcare clinic using discrete-event simulation. *Health Care Manag Sci*, 5(2):75–88, 2002.

[220] H. Taha. *Operations research: an introduction*. Prentice Hall; 9 edition, 2010.

[221] E. Tànfani and A. Testi. A pre-assignment heuristic algorithm for the Master Surgical Schedule Problem (MSSP). *Annals of Operations Research*, pages 1–15, 2010.

[222] H. Tarakci, Z. Ozdemir, and M. Sharafali. On the staffing policy and technology investment in a specialty hospital offering telemedicine. *Decision Support Systems*, 46(2):468–480, 2009.

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

[224] A. Testi, E. Tanfani, and G. Torre. A three-phase approach for operating theatre schedules. *Health Care Management Science*, 10(2):163–172, 2007.

[225] S. J. Thomas. Capacity and demand models for radiotherapy treatment machines. *Clinical Oncology*, 15(6):353 – 358, 2003.

[226] H. Tijms. *A first course in stochastic models*. John Wiley & Sons Inc, 2003.

[227] P. Troy and L. Rosenberg. Using simulation to determine the need for ICU beds for surgery patients. *Surgery*, 146(4):608–620, 2009.

[228] W. Tunnicliffe. A review of operational problems tackled by computer simulation in health care facilities. *Health and social service journal*, 90(4702):73–80, 1980.

[229] M. Utley, S. Gallivan, K. Davis, P. Daniel, P. Reeves, and J. Worrall. Estimating bed requirements for an intermediate care facility. *European journal of operational research*, 150(1):92–100, 2003.

[230] M. Utley, S. Gallivan, T. Treasure, and O. Valencia. Analytical methods for calculating the capacity required to operate an effective booked admissions policy for elective inpatient services. *Health care management science*, 6(2):97–104, 2003.

[231] N. Van Dijk and N. Kortbeek. Erlang loss bounds for OT–ICU systems. *Queueing Systems*, 63(1):253–280, 2009.

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

[233] M. Van Houdenhoven, J. van Oostrum, G. Wullink, E. Hans, J. Hurink, J. Bakker, and G. Kazemier. Fewer intensive care unit refusals and a higher capacity utilization by using a cyclic surgical case schedule. *Journal of critical care*, 23(2):222–226, 2008.

[234] J. van Oostrum, M. Van Houdenhoven, J. Hurink, E. Hans, G. Wullink, and G. Kazemier. A master surgical scheduling approach for cyclic scheduling in operating room departments. *OR spectrum*, 30(2):355–374, 2008.

[235] P. VanBerkel and J. Blake. A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. *Health care management Science*, 10(4):373–385, 2007.

[236] P. Vanberkel, R. Boucherie, E. Hans, J. Hurink, and N. Litvak. A Survey of Health Care Models that Encompass Multiple Departments. *International Journal of Health Management and Information*, 1(1):37–69, 2010.

[237] C. Vasilakis and E. El-Darzi. A simulation study of the winter bed crisis. *Health Care Management Science*, 4(1):31–36, 2001.

[238] C. Vasilakis, B. Sobolev, L. Kuramoto, and A. Levy. A simulation study of scheduling clinic appointments in surgical care: individual surgeon versus pooled lists. *Journal of the Operational Research Society*, 58(2):202–211, 2007.

[239] I. Vermeulen, S. Bohte, S. Elkhuizen, H. Lameris, P. Bakker, and H. Poutré. Adaptive resource allocation for efficient patient scheduling. *Arificial Intelligence in Medicine*, 46(1):67–80, 2009.

[240] S. Villa, M. Barbieri, and F. Lega. Restructuring patient flow logistics around patient care needs: implications and practicalities from three critical cases. *Health care management science*, 12(2):155–165, 2009.

[241] J. Vissers. Patient flow-based allocation of inpatient resources: a case study. *European journal of operational research*, 105(2):356–370, 1998.

[242] J. Vissers and R. Beech, editors. *Health Operations Management: Patient Flow Logistics in Health Care*. Routledge Health Management. Routledge, 2005.

[243] J. Vissers and J. Wijngaard. The outpatient appointment system: Design of a simulation study* 1. *European Journal of Operational Research*, 3(6):459–463, 1979.

[244] R. Wachtel and F. Dexter. Tactical increases in operating room block time for capacity planning should not be based on utilization. *Anesthesia & Analgesia*, 106(1):215, 2008.

[245] L. Walts and A. Kapadia. Patient classification system: an optimization approach. *Health Care Management Review*, 21(4):75, 1996.

[246] Web of Science (WoS). *Retrieved August 10, 2010, from: http://www.isiknowledge.com/*, 2010.

[247] E. Weiss. Models for determining estimated start times and case orderings in hospital operating rooms. *IIE transactions*, 22(2):143–150, 1990.

[248] E. Weiss and J. McClain. Administrative days in acute care facilities: A queueing-analytic approach. *Operations Research*, 35(1):35–44, 1987.

[249] J. D. Welch and N. J. Bailey. Appointment systems in hospital outpatient departments. *The Lancet*, 259(6718):1105 – 1108, 1952.

[250] G. Werker, A. Sauré, J. French, and S. Shechter. The use of discrete-event simulation modelling to improve radiation therapy planning processes. *Radiotherapy and Oncology*, 92(1):76–82, 2009.

[251] F. Wharton. On the risk of premature transfer from coronary care units. *Omega*, 24(4):413–423, 1996.

[252] S. Williams. How many intensive care beds are enough? *Critical care medicine*, 11(6):412, 1983.

[253] W. Winston. *Operations research: applications and algorithms*. Duxbury Press, 2003.

[254] D. Worthington. Queueing models for hospital waiting lists. *Journal of the Operational Research Society*, 38(5):413–422, 1987.

[255] D. Worthington. Hospital waiting list management models. *Journal of the Operational Research Society*, 42(10):833–843, 1991.

[256] P. Wright, K. Bretthauer, and M. Côté. Reexamining the Nurse Scheduling Problem: Staffing Ratios and Nursing Shortages*. *Decision Sciences*, 37(1):39–70, 2006.

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

[258] W. Zijm. Towards intelligent manufacturing planning and control systems. *OR Spectrum*, 22(3):313–345, 2000.

[259] M. E. Zonderland, F. Boer, R. J. Boucherie, A. de Roode, and J. W. van Kleef. Redesign of a university hospital preanesthesia evaluation clinic using a queuing theory approach. *Anesth Analg*, 109(5):1612–1614, 2009.

[260] M. E. Zonderland, R. J. Boucherie, N. Litvak, and C. L. A. M. Vleggert-Lankamp. Planning and scheduling of semi-urgent surgeries. *Health Care Management Science*, 13:256–267, 2010.