Chapter 7
Human and Artificial Scheduling System for Operating Rooms

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Abstract Operating theatres experience dynamic situations that result from unanticipated developments in scheduled cases, arrival of emergency cases and the scheduling decisions made during the day by the operating room coordinator (ORC). The task of the ORC is to ensure that operating rooms (ORs) finish on time and that all scheduled cases as well as the emergency cases are completed. At the end of each day, however, ORs may finish too early or too late because cases have experienced delays or been canceled. Delays or cancelations add to the patient's inherent anxiety associated with surgery and engenders anger and frustration. They have been shown to be an important determinant of patient dissatisfaction across the continuum of preoperative-operative-postoperative care. Recent research (Stepaniak et al. (2009) Anesth Analg 108:1249–1256) addresses how the risk attitude of an ORC affects the quality of the scheduling decision making. In this chapter you will learn about the interaction between the personality of both a human and an artificial OR scheduler, learn about the effects on the decision the OR scheduler makes and the quality of the resulting OR schedule. Therefore, we formalize risk attitudes in heuristics developed to solve the real-time scheduling problems ORCs face during the day.

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7.1 Introduction

Operating rooms (ORs) are relatively scarce resources. Poor scheduling and misuse of ORs can provide opportunities for conflict and competition. Hospital management determines the available operating room (OR) capacity and assigns capacity to the different medical specialties. Increases in the efficiency of use of the ORs results in more production and therefore more revenue for the hospital. However, increasing this efficiency is sometimes easier said than done. Picture the following not uncommon situation. Due to poor case scheduling, OR staff is forced to stand around idly, and expensive nursing, anesthesia and support staff are wasted on some days. On other days, the OR staff works beyond regular working hours to finish the workload on that day. There are situations where surgeons/anesthesiologists arrive too early or too late in the OR and teams are not always ready at the scheduled time. Sometimes the capacity in the OR is insufficient for patients who arrive in the emergency department, which causes scheduled patients to be denied surgery that day, or for staff to work late. Such situations frequently result in nurses, doctors, management and patients becoming extremely frustrated. When looking at an OR in an era in which both cost-containment and quality of health care are considered of prime importance, hospitals simply have to utilize ORs effectively and efficiently. An important tool to achieve this goal is well-designed scheduling systems.

This handbook offers guidance on how to improve health care by improving the delivery of services through application of state-of-the-art scheduling systems. For instance, capacity planning, scheduling patients, staff and nurses are addressed. Every chapter has in common that whatever scheduling system has to be implemented on a day-to-day, hour-to-hour or second-to-second basis, a decision is made by a human being: a scheduler. In this chapter you will learn about the relations between the personality of an OR scheduler, the decision the OR scheduler makes and the quality of the resulting OR schedule. The methods, materials and results in this chapter are based on published scientific publications (Stepaniak et al. 2009; Stepaniak 2010).

7.2 Problems and Formulations

7.2.1 Surgical Case Scheduling

In this chapter, we will consider 'surgical case scheduling' as the process of assigning a given set of cases for a certain day to ORs and defining start times for these cases, in order to maximize OR efficiency (or to minimize OR inefficiency). We can view this as a two-stage process.

The first stage of this process consists of a pre-assignment of one or more days in advance. In this stage, there is much scheduling flexibility since both patients and personnel are not yet informed on their detailed planning. However, after the schedule has been created, it is communicated to all people involved.

The second stage then takes place during the day of operation. Unexpected events (cases may take far more time than scheduled; cases can be cancelled due to no-show or the patient not being ready for surgery) may force the schedule to be revised. Another possibility is the arrival of an emergency case that needs to be added to the schedule as quick as possible. Both types of events can influence the start times of other cases. Also, it might be necessary to exchange cases between ORs. In the end, these changes will also influence the time at which the last case in each room is finished. When cases are still waiting after the regular operating hours, they may be assigned to the service room where an extra stand-by team is available to perform these last cases.

In order to optimize the schedules, decisions made in the first stage should already take into account the events that may occur in the second stage, although exact information about these events is not available. The same is true for decisions made in the second stage: when reacting to a case taking more time than expected, one also has to consider the possibility of an emergency case arriving later that day.

We will define this scheduling process and the measure of inefficiency in a more formal way in Sect. 7.3.

7.2.2 Planning Framework

The flow of activities in the OR through surgical case planning, directing and controlling, and then back to planning again can be formalized by a planning and control cycle. Because there are some differences between industry and service-oriented industries (Vissers and Beech 2005; Morton 2009; Royston 1998; Delesie 1998) a production control framework for hospitals has been developed, which is illustrated in Fig. 7.1 Production control framework. Characteristic for this framework is that patients, processes and chains are the basis for organizing care and it deals with balancing effective, efficiency and timely care. The framework is based on an analysis of the design requirements for hospital production control systems (de Vries et al. 1999; Vissers et al. 2001) and builds on the production control design concepts developed (Bertrand et al. 1990). It is then applied in the context of the OR.

In this chapter the decisions made on the first four levels of the model are given. The focus of this chapter is on the fifth level of the production control framework as applied to the OR. This level concerns the actual scheduling of patients, given planning rules and service requirements for the coming days or weeks. In addition, we look at the process of rescheduling cases in reaction to unforeseen events like delays and arrival of emergency cases. We consider processes used in facilitating day-to-day activities that need to be performed to deliver timely, effective and efficient care for the patient.

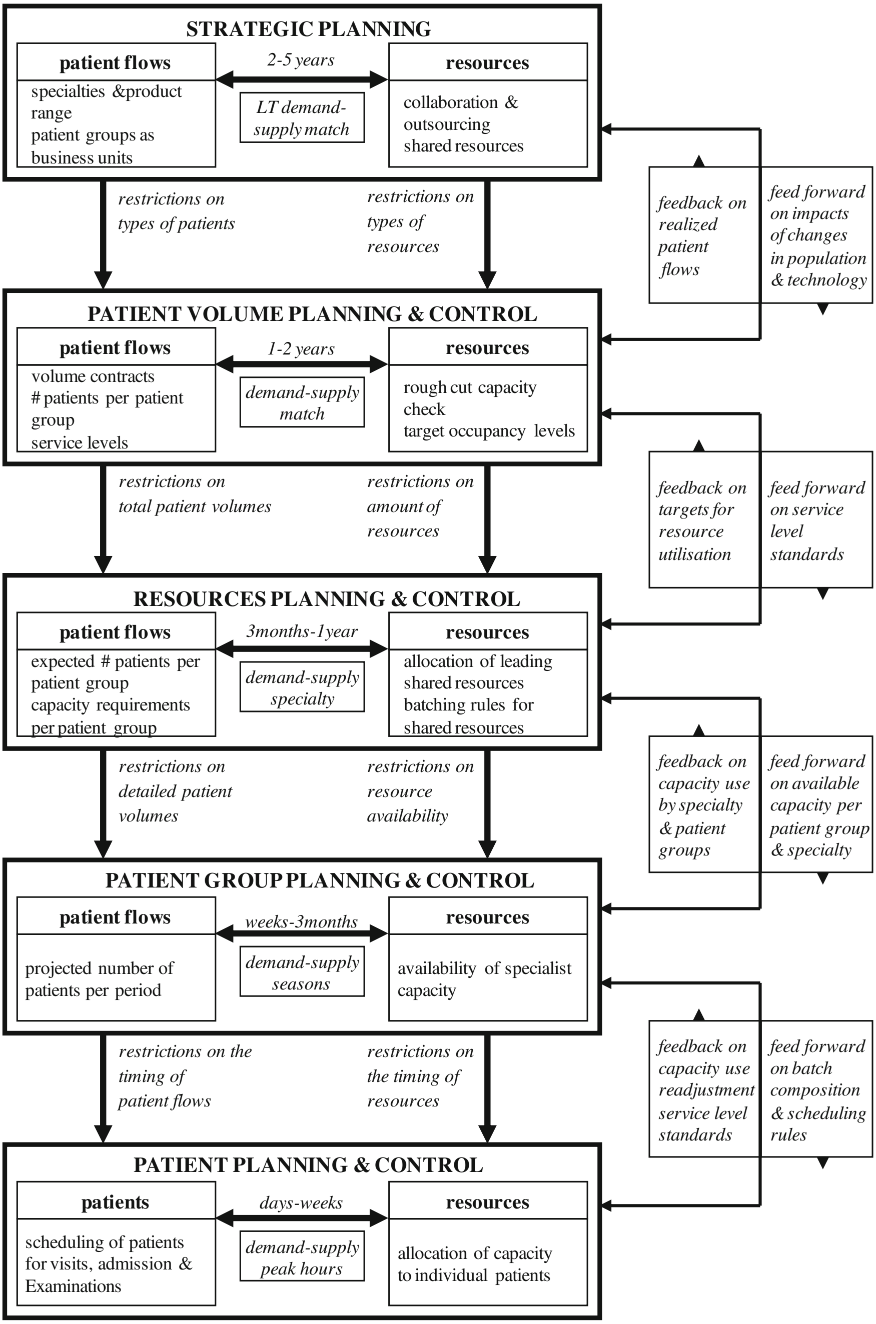


Fig. 7.1 Production control framework

7.2.3 Relevance

Surgical delay has been shown to be an important determinant of patient satisfaction across the continuum of preoperative-operative-postoperative care (Tarazi et al. 1998). Delays in scheduled surgical cases affect patient satisfaction even more than the intraoperative anesthesia experience (Brown et al. 1997).

Delays in surgery resulting from cancellations, bumping of cases and poor scheduling can have a significant impact on the quality of care for scheduled cases as well (Reason 2005). Delays only add to the patient's inherent anxiety associated with surgery and engender anger and frustration. The OR, by its very nature, is an extremely stressful, uncertain, dynamic and demanding environment where staff members need to manage multiple highly technical tasks, often simultaneously (Reason 2005; Silen-Lipponen et al. 2005). Other factors also impact the system within the OR. Examples are individual, group and organizational performance issues such as team and time management, interpersonal skills, leadership, workload distribution, dynamic decision making, human machine interface, problem detection, capture of errors (slips, mistakes, fixation bias), loss of situational awareness, high mental and physical workload, fatigue, environmental stress, production pressure and personal life stress (Weinger et al. 1990). Moreover, the dynamics of the OR are complex because they form a point of intersection among multiple groups with their own agendas and requirements.

OR staff carry out their sometimes long working days under time pressure. The Joint Commission on the Accreditation of Healthcare Organizations has identified time pressures to start or complete the procedure as one of four contributing factors to increased wrong site surgery (ACOG Committee Opinion 2006). Similar to other professions, the undue pressures of time that result from falling behind create stress that can lead to cutting corners or inadvertent error. Relative to other hospital settings, errors in the OR can be catastrophic (i.e., wrong site surgery, retained foreign body, unchecked blood transfusions). In some cases these errors can result in high-profile consequences for the patient, surgeon or hospital (Makary et al. 2006). In other words, poor scheduling and the subsequent induced variations in processes harm outcomes.

Based on the time required to construct schedules as well as the quality of resulting schedules (Beaulieu et al. 2000; Carter and Lapierre 2001) evidence indicates that case scheduling in practice often is performed poorly (Litvak and Long 2000; McManus et al. 2003). Additionally, methods that improve the reliable estimate of surgical cases naturally lead to improved timeliness, efficiency, and effectiveness of OR processes (Dexter 2000; Dexter et al. 2001, 2003; Lapierre et al. 1999; Wickizer 1991).

Reasoning along these lines, Edwards Deming concluded that the real enemy of quality is variation in processes. A main objective in operations management is therefore to identify sources of variation (Tannat 2002). Although variation exists in every process and always will, controlling the identified variation helps managers and clinicians to improve efficiency by aligning the health service delivery processes towards the desired results (McLaughlin and Kaluzny 2006). Indeed, an OR scheduling process that reduces the census variability of the OR can improve the flow of surgical patients to downstream inpatient units, resulting in a more even and predictable patient care burden (Litvak et al. 2005). Furthermore, accurate preoperative scheduling of surgical episodes is critical to the effort to minimize variability in the length of the surgical day and to maintain on-time starts for cases to follow (Litvak et al. 2005).

7.2.4 Formal Problem Definition

We will now turn to a more formal definition of the surgical case scheduling problem. In our definition, the input of the problem consists of:

- A set of n ORs $\{1 \ldots n\}$. A subset of these rooms is available for emergency cases. One room is designated as the service room. All cases starting after time T need to be performed in this room.
- A set of case types. For each case type, we have an estimate of the stochastic distribution of the case durations. In this chapter, we assume that these durations follow a log-normal distribution with two parameters. A subset of these case types are emergency case types. The arrivals of each emergency case type follow a stochastic process.
- A set of cases C that can be divided into the set of elective cases and a set of emergency cases. Notice that the emergency cases are not part of the problem's initial input. These cases are implicitly defined by the arrival processes of the emergency case types. They become known only at the time of arrival. The duration $d(c)$ of each case $c \in C$ is only known when the case finishes.
- Regular working hours during which all ORs are opened. We assume they open at time 0 and close at time T. Any cases that have started before T are guaranteed to finish, even if this means that the room has to stay open after T.

In the first stage, each case is assigned an OR and a start time. In the second stage, these assignments can be changed when necessary. Eventually these actions lead to the actual start and end time of the individual cases as well as the closing times C_i of each room i The inefficiency measure discussed earlier can then be defined as $Eff = \sum_i (T - C_i)^+ + \beta \cdot \sum_i (C_i - T)^+$ where $(x)^+ = \max(x, 0)$ and β is the relative cost of overtime.

The objective function can be modified in several ways if we include additional scenarios. First, elective cases can be canceled if not enough regular time is available. We define the set $C^c \subseteq C$ of canceled cases and incur a penalty for each canceled case, which is proportional to the length of the case: $\alpha \cdot \sum_{c \in C^c} d(c)$. Also, for emergency cases we introduce the requirement that they are started within a certain time limit. For each case that violates this requirement, we incur a fixed penalty δ. Let the violating cases be collected in set C^v; then the total penalty value becomes $\delta \cdot |C^v|$.

Having specified the input and the objective function, we now turn to the constraints of the problem, thus defining the solution space available to the Operating Room Coordinator (ORC). First, we assume that the assignment of scheduled cases is given, as is the linear order of the cases per OR. Thus the order of the cases cannot be modified, except for the insertion of emergency cases. Emergency cases can only be scheduled in dedicated ORs, which typically have slack time to accommodate emergency cases. Cases that have already started cannot be interrupted (preempted) for emergency cases. Further, emergency cases cannot be canceled. When a case for an OR is canceled, it is the last scheduled case in the linear order of cases assigned to that room. As an alternative to being cancelled, the last scheduled case can be moved to the service OR to be scheduled after time *T*. Cancelation and referral decisions cannot be undone. The schedulers do not have information about future arrivals of emergencies or durations of cases other than the information described in the problem input.

7.3 Prior Research

The scheduling of patients in the OR has been studied extensively over the past 40 years. In a review of surgical suite scheduling procedures, Magerlein and Martin (1978) discuss methods for planning patients in advance of their surgical dates, as well as techniques for assigning patients to ORs at specific times of a day. Dexter et al. (1999a, b) used online and offline bin-packing techniques to plan elective cases and evaluated their performances using simulation. A goal-programming model to allocate surgeries to ORs is explored by Ozkarahan (2000). Marcon et al. (2003) present a tool to assist in the planning negotiation between the different actors of the surgical suite. Linear programming models have also been proposed for the planning and scheduling of ORs' activities (Guinet and Chaabane 2003; Jebali et al. 2005). Fei et al. (2004) proposed a column generation approach to plan elective surgeries in identical ORs. Lamiri et al. (2008) present an optimization model and algorithms for elective surgery planning in ORs with uncertain demand for emergency surgery. Their problem consists of determining a plan that specifies the set of elective cases that would be performed in each period over a planning horizon (1 or 2 weeks). The surgery plan should minimize costs related to the over-utilization of ORs and costs related to performing elective surgeries.

The problem addressed in this chapter is related to scheduling problems in which the objective is a weighted function of the makespan and penalties for rejected cases. Such scheduling problems with rejection have been studied for various single objective functions, finding a single optimal solution for case scheduling.

Charnetski (1984) uses simulation to study the problem of assigning time blocks to surgeons on a first-come, first-served basis when the goal is to balance the waiting cost of the surgeon and the idle cost of the facilities and operation room personnel. The proposed heuristic recognizes that different types of procedures have different service time distributions and sets case allowances based on the mean and standard deviation of the individual procedure times. Dexter et al. (1999c) uses computer-based hypothetical OR suites to test different OR scheduling strategies aimed at maximizing OR utilization. OR utilization depends greatly on (and increases) as the average length of time patients wait for surgery increases.

In Van der Velden (2010), methods are developed that take into account multiple objectives. Also, classification trees are used to partition a set of input cases into different subsets and determine optimal heuristics for each subset.

7.4 Applications

We have observed that the personalities of ORCs differ among hospitals in relation to the ORCs willingness to take on more risk in their daily planning, with respect to the risk of cases running late but filling more gaps. This was our motivation for analyzing the effect of risk aversity of an ORC on OR efficiency.

7.4.1 About the Operating Room Coordinator

The person responsible for the surgical schedule is the ORC. The ORC observes the daily variation in this schedule and takes the necessary actions such that scheduled and non-scheduled cases are performed without ending too late in too many ORs at the end of the day. ORCs are the people who maintain a safe and orderly flow of patients in the OR. The position of the ORCs is one that requires highly specialized skills. Moreover, the job can be notoriously stressful, depending on many variables (equipment, specialist, arrival of emergency/acute cases, delay in schedules, human factors, communication, etc.). In addition, they are generally assertive but calm under pressure, and they are able to follow and apply rules and yet be flexible when necessary. The ORC starts with a given schedule and deals with the turn of events as it materializes while performing scheduled cases and emergency cases as they newly arrive. Their jobs involve frequent communication with the various stakeholders such as anesthetists, surgeons and other OR staff. The ORC may cancel scheduled cases, or defer them to the service OR. Their responsibilities include rearranging case and staff assignments, as some OR cases take more or less time than originally planned, and unplanned acute patients require surgery. All other cases have to be performed, potentially yielding overtime work. The task of the ORC is therefore to balance the costs of working overtime with the effects that cancellations have on patient satisfaction and patient health.

There are observed differences among the personalities of the ORCs with regard to their willingness to accept more risk concerning their daily planning. The hypothesis is tested that the relationship between the personality of an ORC, and especially the risk an ORC is willing to take of cases running late, influences OR efficiency. In this section, we discuss an empirical test performed on the ORCs. In Sect. 7.6, we turn to a simulation model developed to test a large range of risk attitudes on an extensive data set. We will use data from the Sint Franciscus Gasthuis (SFG), Rotterdam, The Netherlands.

7.4.2 Human Risk Attitudes

A decision maker is said to be risk-averse if he prefers less risk to more risk, all else being equal. In the OR, a risk-averse decision maker wants all the ORs to be finished before the end of the working day without any chance of running late. The opposite of risk aversion is risk-seeking. A risk-seeking decision maker will prefer more risk to less risk, and accepts the possibility of running late, all else being equal.

There are numerous contributions to the conceptualization of subjective orientation toward risk (Sitkin and Pablo 1992; Weber et al. 1998; Trimpop et al. 1999). Some studies analyze the interaction between personality feature variables, which are not risk attitudes. These variables have been linked to decision-making on risky courses of action (Zuckerman 1990), impulsiveness (Eysenck and Esenck 1977) and decision-making style (Franken 1988). Zuckerman (1994, 2002) developed the Zuckerman–Kuhlman Personality Questionnaire (ZKPQ) to assess personality along five-dimensions. The results of the ZKPQ have been replicated across several studies. These results have shown for example that risk-taking is related to scores on the ZKPQ impulsive sensation seeking scale (Zuckerman 1990). Zuckerman (1990, 2002), Zuckerman and Kuhlman (2000) defines sensation seeking as a need for new and complex experiences and a willingness to take risk for one's own account. He has found that high sensation seekers tend to anticipate lower risk than low sensation seekers do, even for new activities. This finding indicates that a high sensation seeker is more likely to look for opportunities that provide the chance to take a risk, and that the will to take risks seems less threatening to this specific type of individual.

To assess personality versus risk-taking relationship of an ORC, the ZKPQ test and subsequent scores can be applied. We have performed this calculation for the ORCs at the SFG. ZKPQ scores on impulsive sensation seeking can be grouped as follows: the scores of very low and low were considered to be risk-averse, the average scores were considered risk-neutral and the high and very high scores were considered to be non risk-averse. In 2006, prior to the start of the study, the ORCs in the SFG were informed about this study, whereas in 2007 they were not. The ZKPQs for every ORC are given in Table 7.1.

7.4.3 Analyzing Differences Between Risk Attitude Groups

In order to analyze which risk attitude creates maximum OR efficiency, the ORCs expectations with regard to how the OR program would materialize is registered every working day. This expectation, or prognosis, is proposed by the ORC and he

Table 7.1 ZKPQ score per ORC

ORC	ZKPQ score (%)
#1	81
#2	92
#3	25
#4	32

informs the anesthetist on duty of this. When making the prognosis, the following aspects are estimated and noted by the ORC:

- Which OR(s) need(s) time after business hours;
- Which OR(s) are on schedule;
- The amount of available OR capacity for emergency surgery during the period from 2 PM until 4 PM. This capacity is designated for patients already on the waiting list and for emergency patients outside or inside the hospital who may possibly need emergency/acute surgery.

If at 4 PM, all the above-mentioned aspects have been accurately estimated, we say that the ORCs prognosis has materialized. In all other cases, the prognosis has not materialized. Further we measured:

- Whether the prognosis of the ORC made at 2 PM coincides with the actual situation at 4 PM (% of all prognoses made);
- Accurate prognosis made at 2 PM that specific ORs would need extra time after regular working hours (% of all prognoses made);
- The average end time of all ORs;
- The average end time of all ORs still running after 4 PM;
- The average number of ORs in progress after 4 PM;
- The number of unnecessary rejections of planned elective patients.

Operating room inefficiency is defined as the sum of under-utilized OR time and over-utilized OR time multiplied by the relative cost of overtime (Dexter et al. 2004). This definition takes into account the negative effects of not using the expensive operating theatres and having to work outside regular working hours.

The significance of the difference in the average end of program time between risk-averse and risk-seeking ORCs is tested using a factorial ANOVA ($p = 0.05$). After filling in the ZKPQ test and measuring the outcomes during a five month period, the results are as in Table 7.2, which shows the quantitative results of the two groups in 2009–2010.

We observe that the non risk-averse ORC makes a better prognosis concerning the development of the OR program. The average end times of the OR are almost 30 min later compared to the risk-averse ORs. The number of rejected patients is lower when a non risk-averse ORC makes decisions. Further, between the ORCs there is no difference in the average end times of ORs after 4:00 PM.

We studied the sample variance among OR-day combinations. For the study period we used Levene's test of homogeneity of variances. With $p = 0.865$ (2008)

Table 7.2 Main results per type ORC per study period

Working days	Non risk-averse		Risk-averse	
	2009 119	2010 121	2009 120	2010 122
The prognosis of the ORC made at 2 PM matches the actual outcome at 4 PM (% of all prognoses made)	84	81	48	58
Accurate prognosis made at 2 PM that specific ORs will require extra time after regular working hours (% of all prognoses made)	84	79	31	41
Average end time all ORs	3.51 PM (±9 min)	3.42 PM (±11 min)	3.18 PM (±11 min)	3.21 PM (±14 min)
The average end time of all ORs still running after 4 PM	4:20 PM (±18 min)	4:18 PM (±14 min)	4:16 PM (±17 min)	4:19 PM (±17 min)
The average number of ORs in progress after 4 PM (%)	13.8 (±2.5)	11.3 (±2.5)	8.8 (±1.3)	11.3 (±3.8)
The number of unnecessary rejections of planned elective patients	7	9	19	22

and $p = 0.213$ (2009), we can conclude that in both study periods we have equal variances. We performed the one-way ANOVA to compare means of case duration of the four ORCs. With a p value of 0.583 we accept the hypotheses of equal means for the case duration for the four ORCs.

Based on the results we calculated the mean inefficiency per OR per day by considering each OR-day to be independent of all others. The relative cost of overtime in our study is 1.50. The cost per hour of over-utilized OR time includes: indirect costs, intangible costs, and retention and recruitment costs incurred on a long-term basis from staff working late. The mean inefficiency per OR per day for the risk-averse ORC is 0.86 (SD 0.24). For the non risk-averse ORC, the mean inefficiency per OR per day is 0.42 (SD 0.18). This means that the non risk-averse ORC causes a lower OR inefficiency.

7.4.4 Modeling Risk Aversity in Scheduling Algorithms

The research described in the previous section confirms our presumption that risk aversity leads to inefficiency. However, since the number of ORCs in a hospital is limited, it is hard to obtain enough data for a more extensive test. We have therefore developed a simulation model that allows us to measure the impact of risk attitude on the number of canceled tasks, overtime and inefficiency.

Simulation Model

We simulate separate, independent working days using discrete event simulation: the system is modeled by means of a chronologically ordered discrete set of events. As these events are processed one at a time, the state of the system changes and new events may be generated. The simulation starts at 8:00 a.m. and ends when all regular ORs have completed their final case. Because we compare the simulation results with real life day-per-day data from the SFG, we have chosen not to consider interdependencies between working days, e.g., by rescheduling canceled cases the next day.

In each room, we start the first case at 8:00 a.m. When a case starts, the corresponding 'finish event' is generated using the historic duration of the case (so that we can compare our outcomes with historic data). Of course the rescheduling heuristics do not use this generated duration, but work with the parameters of the distribution of the duration of cases of that type. After a case has finished, 9 min is scheduled for cleaning time. After cleaning, the next case assigned to the room starts as soon as possible (if there is one). Cases cannot start more than 60 min earlier than scheduled.

During the simulation, an artificial ORC makes decisions that may change the schedule. For reasons of computation times, we have limited the frequency by which rescheduling is considered. A first rescheduling occurrence is at 8 a.m. when the newly arrived cases are considered, possibly leading to modifications of the original schedule. During the day we consider rescheduling whenever a case finishes with an ending time that differs 15 min or more from the scheduled ending time. Rescheduling is also considered when a new emergency case arrives, and at 16.00, the scheduled closing time of the ORs. Finally, rescheduling is considered at least every 60 min.

Rescheduling must take the following rules into account:

- The sequence of elective cases within an OR is fixed and cannot be changed during the day.
- When an emergency/acute case arrives, it is placed in the series 'non-scheduled'. There is no room assigned to this specific case.
- If before 4 p.m. there is OR capacity available in a room then the next scheduled elective case or urgent/acute case is started.
- Scheduled cases can be moved from the originally assigned room to the service OR or can be canceled.
- Cases that are not yet assigned to any room can be assigned to a room or to the service (so that they are performed after 4 p.m.).

- Canceled cases or cases moved to the service OR cannot be scheduled again in the day schedule (before 4 p.m.).
- Cases cannot be paused or stopped once they have started

Parameterizing Risk Attitude

To evaluate a feasible decision in our heuristic approach at time t, we sample a fixed number of scenarios, each of which completely specifies all arrivals of emergency cases after t, and the durations of all cases to be completed after t according to the scheduling decisions made. We define the cost of a scenario by the cost of the optimal solution for the offline problem as specified by a scenario. Since we want to evaluate a feasible solution at time instant t, we in fact consider the conditional cost of a scenario, i.e., the cost of an optimal solution for the scenario, under the condition that the decision under consideration is indeed taken at time t.

We subsequently define risk attitude on the basis of the scenarios that are taken into account when evaluating decisions. Risk averse ORCs are modeled by considering only a subset of scenarios with high conditional cost for the decision under consideration, whereas risk seeking ORCs are modeled by considering only a subset of scenarios that have low conditional cost for the decision under consideration. In the end, both types of ORCs choose the decision that they evaluate as best.

To formalize this idea, consider the outcomes of a decision for a set of M scenarios. To evaluate the decision, a family of functions is used. Each of these functions sorts the costs under the different scenarios and then takes the average of a subset of these sorted costs. Family members differ in the subset that is used and different subsets represent different risk attitudes. The subsets depend on parameters $\varphi \in [0, 1], \omega \in (0, 1)$ as follows. Let x be the vector of sorted outcomes with x_i an element of this vector. We assume x_1 is the smallest cost (best case) and x_M is the largest cost (worst case). For given φ and ω we define a function $f_{\varphi,\omega}(x)$ on the vector x of sorted outcomes as follows:

$$f_{\varphi,\omega}(x) = \frac{1}{\omega M} \sum_{i=1+\lfloor \varphi(1-\omega)M \rfloor}^{\lceil \omega M + \varphi(1-\omega)M \rceil} x_i,$$

which is the average of the outcomes with indices between the boundaries $1 + \varphi(1-\omega)M$ and $\omega M + \varphi(1-\omega)M$, which is an interval containing ωM outcomes.

We have three special cases:

- For $\varphi = 0$ we have $f_{0,\omega}(x) = \frac{1}{\omega M} \sum_{i=1}^{\lceil \omega M \rceil} x_i$, which corresponds to the average of the first ωM elements in vector x.
- For $\varphi = 1$ we have $f_{1,\omega}(x) = \frac{1}{\omega M} \sum_{i=1+\lfloor (1-\omega)M \rfloor}^{M} x_i$, which corresponds to the average of the last ωM elements in vector x.

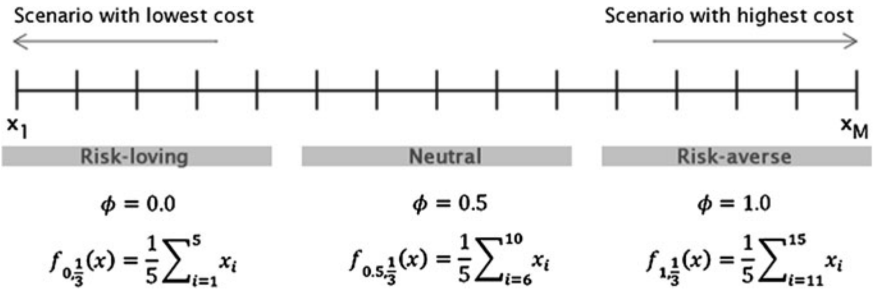


Fig. 7.2 Averaging outcomes

- For $\varphi = 0.5$ we have $f_{0.5,\omega}(x) = \frac{1}{\omega M}\sum_{i=1+\lfloor 0.5(1-\omega)M\rfloor}^{\lceil \omega M+0.5(1-\omega)M\rceil} x_i = \frac{1}{\omega N}\sum_{i=1+\lfloor 0.5M-\omega M\rfloor}^{\lceil 0.5M+0.5\omega M\rceil} x_i$, which corresponds to the average of the middle ωM elements of vector x.

We can view these cases in a more practical, human way:

- A person with $\varphi = 0$ would be a risk seeker, who only takes the best possible outcomes into account and does not care about any scenario that would result in a worse outcome.
- A person with $\varphi = 1$ would be a risk-averse person, whose decisions are guided by worst things that may possibly happen.
- A person with $\varphi = 0.5$ bases his or her decision on the more usual outcomes, ignoring the real extreme cases (good or bad) cases.

This is illustrated in Figure 7.2, where we assume $\omega = 0.3$ and $M = 15$. Note that the three person types all take the average of $\omega M = 5$ observations.[1] However, the non risk-averse ORC averages the five best outcomes while the risk-averse person averages the five worst outcomes. The average person takes some observations in between while ignoring the extreme outcomes on both sides.

The rescheduling heuristic uses Monte Carlo optimization. A Monte Carlo experiment is a class of computational algorithms that relies on repeated random sampling to compute their results. In our study we use it as follows. It starts by generating a set of scenarios. A scenario consists of a random realization for the duration of each of the remaining cases including a set of randomly generated emergency cases still to arrive. For each scenario all assignments of future arrivals to ORs are enumerated. These assignments decisions are complemented by optimal decisions regarding cancelation of elective cases and rescheduling of elective cases in the service OR. Optimality is regarded here with respect to a aforementioned cost function, which serves as the objective function. The cost of a scenario

[1] In the preceding text, we have assumed that all values are integral. In our implementation, we first calculate ωM and round this down; also, the limits for the summation are rounded down

is set to equal the minimum costs (over all assignments for the emergency cases generated in the scenario) of the created optimal schedule per assignment. The rationale behind using the cost of minimum cost schedules for optimal assignments is that this coincides with the scheduling objectives taken into account during the day.

Data and Parameter Settings

The simulation is based on a 3-month period in the year 2009. The total number of surgical cases in this period amounts to 3,027, of which 301 are emergency cases and 39 are acute cases. The number of ORs is ten. For every surgical case we know the scheduled and actual case duration; scheduled and actual start and end time; whether the case is elective, urgent or acute; and the scheduled and actual OR where the case is performed. Holidays and weekends are excluded from the data. Based on the data, all relevant events on the days of surgery and the adjustments can be simulated and the outcomes can be compared to the historical outcomes.

For each surgery we have estimated the parameters of the lognormal distribution that can be used to estimate the case duration. All electives cases were known at 8 a.m., the beginning of the working day. For emergency arrivals, we do not exactly know the time at which they arrived. We will assume the following about their arrival:

- Around 50% of the emergency cases arrive between the end of the previous day and 8:00 a.m. (SFG, 2010). These emergency cases are considered at the start of the day. The remaining emergency cases arrive at a random time between 8 a.m. and 4 p.m.
- The simulation uses historical urgent and acute cases.
- The subset of ORs to which emergency cases can be assigned may vary per day.

To generate random urgent and acute case arrivals between 8:00 and 16:00 for the scenarios, we have collected data about the arrivals of emergency cases in 2008. We assume that the time of day arrivals occur according to a non-homogeneous Poisson process with a piecewise constant arrival rate. The arrival rates are estimated using the mean number of arrivals per 30 min time interval. For each random arrival, we sample a random emergency case from the historical data set. The state of the system at a certain time of the day consists of the status of the planning: the starting and ending times of all cases that have been completed, the starting times and expected duration of the cases that are being performed at that moment, the ordered lists of cases scheduled for future execution in each of the rooms, the list of cases that will be performed in the service OR and finally the list of cases that have been canceled and the cases that have not yet been assigned to any room.

Because SFG aims to avoid cancelation of cases at all costs, we set the corresponding parameter at infinity very large positive value (i.e., $\alpha = 1{,}000{,}000$). In order to find suitable values for the weights β and γ, we have presented actual

ORCs with several dilemmas in which there is a choice between an amount of overtime and another amount of service:

- If there are at 3:30 p.m. two cases to perform, of which one has a scheduled duration of 45 min and the other a scheduled duration of 60 min, which one (or both) of these cases are moved to the service OR?
- Would you rather start a very important case with a scheduled duration of 140 min in the scheduled OR at 2:50 p.m. or at 4 p.m. in the service OR? And would you start the same case at 2:20 p.m. in the scheduled OR or at 4 p.m. in the service OR?
- Would you prefer to perform a case with a scheduled duration of 90 min in the service OR, or would you rather schedule this very same case in a OR with only 60 min of capacity left? And, what would you do if only 45 min of capacity is left?

We suppose that the one who is answering a question balances two types of costs: cost of overtime and costs of moving the operation to the service OR. Let us look at the first question in the third bullet. Suppose that the ORC decides to schedule the case in an OR with only 60 min of capacity left. The ORC prefers 30 (90−60) min expected overtime above 90 min service time. To state it differently, the costs assigned to 30 min of overtime are lower than the costs of 90 min operating in the service OR. Then 30 min x cost overtime <90 min x cost of service time. Then the cost ratio of overtime to service time is <3. We can conclude that the ORC prefers overtime more than three times over service time. Based on the choices made by the ORCs, we set $\beta = 2$ and $\gamma = 1$ (i.e., 1 min of overtime is twice as costly as 1 min of work in the service room). In our experiments, we have considered 30 scenarios while evaluating each possible decision. The choice of 30 scenarios is based on the fact that in real life a rational choice takes into account the cognitive limitations of both knowledge and cognitive capacity of the human being (Simon 1991).

7.4.5 Simulation Results

It is interesting to find out the effects of different risk attitudes when we assume that human capacity will have a hard time analyzing a large number of scenarios. Therefore, in our comparison of simulation results with the historic outcomes, we will use a simulation with 50 scenarios. We now present the results (*based on 50 scenarios*) in comparison with the historical data in Table 7.3.

The last column gives the historical results. The three preceding columns give the results for various choices of the risk aversion parameter φ. The first column are the result for $\varphi = 0$, the most risk seeking variant. The next columns use $\varphi = 0.5$, and $\varphi = 1$, the most risk-averse variant. The simulation results show that the process of cancelation works realistically. At the same time, it reveals that the

Table 7.3 Comparison between results simulator and historical data

	Non risk- averse policy	Mean policy	Risk-averse policy	Historical results
Rejected cases	24	27	30	25
Overtime (min)	5,238	4,060	4,745	2,291
Service time (min)	9,121	10,964	11,269	12,871
Value objective function	24,019,597	27,019,084	30,020,759	25,017,453

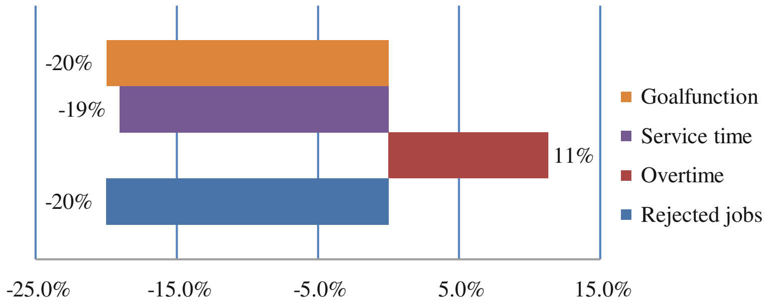


Fig. 7.3 Effect of non risk-averse policy as compared to risk-averse policy (based on 50 scenarios)

preferences regarding overtime versus referral to a service OR may work differently in practice than stated by the ORCs in the presented dilemmas.

The modeling of risk aversion is especially interesting as it models the effect of variations of risk attitude between ORCs. Figure 7.3 compares the results of a risk-minded heuristic ($\varphi = 0$) with a risk-averse heuristic ($\varphi = 1$). The risk-minded heuristics result in less service time, less cancellations and a better objective function value. It does, however, generate more overtime.

Because the SFG specifically wants to avoid cancelation of cases at all costs, α was set at a relatively large value (1,000,000). As there are many hospitals there may be different approaches towards cancelation of cases. To make a more general analyses we therefore set α (arbitrally) tot 100. Figures 7.4, 7.5 and 7.6 show the results of this more general analysis of how each of the three objective function components varies in value with φ. We see the same trend concerning the effect and direction of different risk attitudes on the three components of the goal function as in Table 7.3, but with different values.

We clearly see that risk aversion leads to an increase in the number of cancellations, increase in service time and decrease in overtime. A risk-averse person focuses on the worst scenarios (which may include a larger number of emergency case arrivals or longer expected case durations). Since service time is limited, the presumption of an increased workload will lead to more cancellations.

Fig. 7.4 Risk aversion versus rejected patients

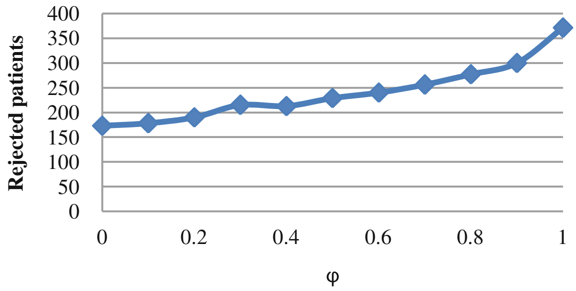


Fig. 7.5 Risk aversion and overtime

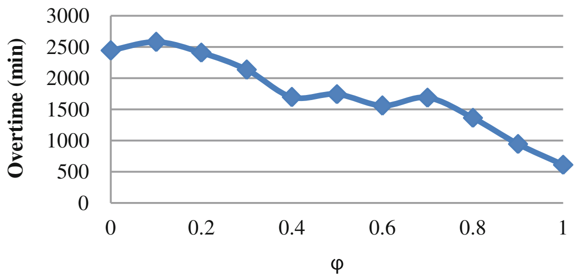
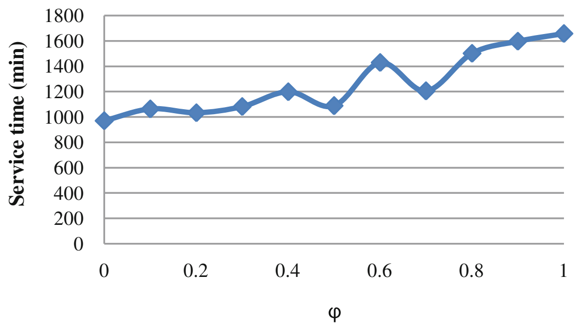


Fig. 7.6 Risk aversion and service time



7.5 Further Research

We modeled the daily dynamics faced by the OR and especially how risk aversion influences the quality of the scheduling decisions. Our results are consistent with the findings in the literature: a high sensation seeker is likely to look for opportunities that provide the chance to take a risk, and this risk will seem less threatening to this kind of individual. The results confirm earlier findings that a non risk-averse ORC creates lower costs and fewer rejected patients compared to a risk-averse ORC as well as a higher utilization during working days. When recruiting an ORC, it may be helpful to consider risk-aversion one of the selection criteria.

Though there is much evidence to support the link between personality and risk-taking, the literature shows that the exact nature is still unclear. It could be interested to find what happens in the mind of a risk-taker that is significantly different from what occurs in the mind of a non risk-taker. Further, in our research we choose one axis of interest: sensation seeking. But there are other axes, such as neuroticism-anxiety, aggression-hostility, activity, and sociability that can be important, necessary, or completely determinative for an ORC's success in planning the schedule. This has to be analyzed in future studies with a larger population of ORCs. We suggest repeating the study in other hospitals and further improvement of the heuristics in the process. More generally, improvement of the heuristics is an interesting direction for further research. The results of these research will contribute to improved timeliness, efficiency, and effectiveness of OR processes.

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