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Abstract Due to surgery duration variability and arrivals of emergency surgeries, the planned Operation Room (OR) schedule is disrupted throughout the day which may lead to a change in the start time of the elective surgeries. These changes may result in undesirable situations for patients, wards or other involved departments, and therefore, the OR schedule has to be adjusted. In this paper, we develop a decision support system which assists the OR manager in this decision by providing the three best adjusted OR schedules. The system considers the preferences of all involved stakeholders and only evaluates the OR schedules that satisfy the imposed resource constraints. The decision rules used for this system are based on a thorough analysis of the OR rescheduling problem. We model this problem as an Integer Linear Program (ILP) which objective is to minimize the deviation from the preferences of the considered stakeholders. By applying this ILP to instances from practice, we determined that the given preferences mainly lead to (i) shifting a surgery and (ii) scheduling a break between two surgeries. By using these changes in the decision support system, less surgeries are canceled and the perceived workload of all departments is reduced. The system can also be used to judge the acceptability of a proposed initial OR schedule.

Keywords Operating Rooms · Rescheduling · Integer Programming · Decision Support System

1 Introduction

The Operating Room (OR) department is one of the most expensive resources of a hospital. However, managing the OR department is hard due to conflicting priorities and preferences of stakeholders. Therefore, planning and scheduling methods are needed to increase the efficiency in OR departments. See Cardoen et al. [2] and Hulshof et al. [10] for an overview on OR planning and scheduling.

In this paper, we focus on the rescheduling of surgeries, or more precisely, on the rescheduling of surgeries throughout the day. On the one hand, emergency patients who need surgery arrive throughout the day. In many hospitals, these surgeries are scheduled in one of the elective ORs which disrupts the OR schedule. On the other hand, a change in the surgery duration of elective surgeries may also disrupt the OR schedule. Therefore, the initial OR schedule may have to be adjusted throughout the day to ensure that it is still possible to execute the schedule. The new OR schedule must fulfil quite a number of restrictions, and in addition, there are several stakeholders whose preferences and priorities must be met. Since it is hard for an OR manager to consider all these restrictions and preferences simultaneously, we develop a decision support system which supports the OR manager with rescheduling the ORs.

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Most existing literature focuses on operational off-line scheduling instead of operational on-line scheduling. The papers concerning operational off-line scheduling mainly focus on two methods. The first method is reserving time for emergency surgeries to minimize overtime and maximize OR utilization (see e.g. [1], [8] [11]). The second method is sequencing the elective surgeries such that the overtime caused by surgeries with a longer duration than expected is minimized (see e.g. [3], [12], [13]).

One of the papers concerning operational on-line scheduling is the paper by Dexter [4] who examined whether moving the last surgery of the day to another OR could decrease overtime labour costs. The developed statistical strategy was based on historical data. However, in practice, often one surgeon operates in an OR on a day or part of the day and therefore, it is not allowed to move a surgery to another OR.

Dexter et al. [6] introduce four ordered priorities on which an OR management decision for changing the OR schedule can be based. The first and most important priority is patient's safety. The second priority states that a surgery can only be canceled if the patient safety is not accounted for. The third priority is to maximize OR utilization, and the fourth and last priority is to reduce patient waiting times. These priorities, however, put maximizing OR utilization above patients satisfaction. For patients it is not preferred to schedule their surgery earlier and certainly not later in the day. In addition, no priority considers the workload level on other departments like wards, the holding department, and the recovery department.

Another paper of Dexter et al. [5] considers the sequencing of urgent surgical cases. They proposed a sequencing which is based on the following three objectives: (i) minimize the average waiting time of surgeons and patients, (ii) sequence the surgeries in order of appearance, and (iii) schedule the surgeries in order of medical urgency. However, none of these objectives consider the preferences of the elective patients and other departments.

It seems that none of the existing papers on OR rescheduling considers the preferences and priorities of all the stakeholders. This paper tries to fill this gap. In Section 2, we discuss the stakeholders and their restrictions and preferences which are based on a survey performed at the Isala Clinics, a hospital in the Netherlands. Although these restrictions and preferences may differ between hospitals, the principle ideas of the method developed in this paper should be applicable for other hospitals too. The resulting restrictions and preferences are incorporated in an Integer Linear Program (ILP) for the OR rescheduling problem, which has as goal to minimize the deviation from the preferences of the stakeholders. To justify the approach to model the problem as an ILP, we prove that the OR rescheduling problem is NP-hard for two or more ORs. Due to long computing times the developed ILP model cannot be used as part of a decision support system where schedules have to be generated within a short amount of time. However, we use this ILP to derive decision rules for the OR rescheduling problem based on instances of the Isala Clinics. The achieved decision rules are incorporated in the decision support system which is described in Section 4. Section 5 draws conclusions and gives recommendations for further research.

2 Problem Formulation

In this section, we give an introduction to the OR rescheduling problem and we introduce an ILP model which can be used to determine a new OR schedule throughout the day. The ILP includes all relevant constraints that are imposed on the OR schedule; e.g. the availability of a patient, as well as the availability of an OR with OR assistants, a surgeon and an anesthetist. In addition, the capacity of the holding and recovery department are considered. A detailed description of the constraints is given in the following subsections.

The objective of the ILP is to minimize the deviation of the preferences for the involved stakeholders. When the OR schedule deviates from these preferences some penalty costs are incurred and the weighted sum of these penalty costs is minimized. There can be, for example, penalty costs for deviating from the scheduled start time of a surgery or for the amount of resulting overtime. In addition, we minimize the number of canceled patients, as this is not preferred by any of the stakeholders. The developed ILP can also be used to determine whether a proposed OR schedule is feasible or not, and in case it is feasible, to calculate the deviation from the preferences of the stakeholders.

Before we introduce the model, we first give a short description of the process a patient follows on the day of surgery (see Figure 1). On or before the day of surgery, the patient is admitted on a ward where he/she is prepared for surgery. Some time before surgery, the patient is transported to the holding department where the patient is further prepared for surgery. Then, the patient is transported to the operating room where the anesthetist administers anesthesia. After this, the surgeon performs the surgical procedure. When the surgical procedure is finished, the anesthetist reverses the anesthesia, and then, the patient is transported to the recovery department where he/she recovers from the effects of the anesthesia. At the time these effects have

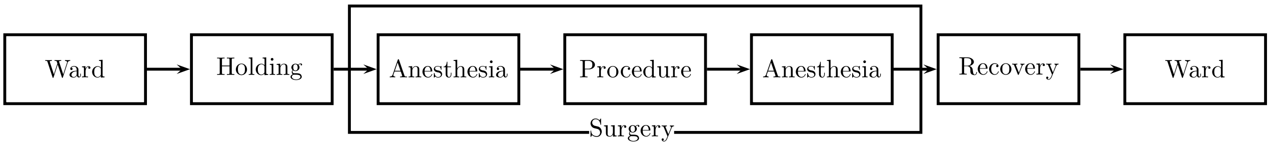


Fig. 1 Patient process

completely worn off and the patient's condition is considered stable, he/she is transported back to the ward.

For the modeling, we discretize an OR-day into T time periods which have a length of δ minutes. The length of one OR-day is therefore δT minutes. We denote by time $t \in T$ the period $((t-1)\delta, t\delta]$. The set of ORs is given by set J and consists of M ORs. The start time of OR $j \in J$ is denoted by S_j and the end time by F_j. The set of surgeries is given by set I and consists of N surgeries. The subset $I_j \subseteq I$ denotes the surgeries that are scheduled in OR $j \in J$ and $O_i \in J$ denotes the assigned OR for surgery $i \in I$.

The initial OR schedule, which is given at the beginning of the day, is defined by the assignment of the elective surgeries to an OR and the initially planned start times P_i of the elective surgeries. Each surgery has an expected duration E_i which includes the time for administering and reversing anesthesia, however, in practice, the duration of a surgery generally deviates from this duration and takes longer or shorter than expected. When a surgery takes less time than expected, and the next surgery starts at its assigned time P_i, the initial OR schedule is not disrupted. However, it may be beneficial for the OR and other departments to schedule this next surgery earlier. When a surgery takes longer than expected, the next surgery may have to start later. This results in a shift of the not yet started surgeries in this OR. Because of this, some resource constraints may be violated. In addition to these deviations of the durations of the elective surgeries, emergency surgeries may arrive which also disrupt the initial OR schedule. Therefore, throughout the day, a new OR schedule may have to be created for all not started elective and emergency surgeries. In the following, we denote by set I the set of all these surgeries. The rescheduling is done by assigning a new start time to each surgery $i \in I$. Formally, this is expressed by binary variables s_{it}, which are one when surgery $i \in I$ starts at time $t \in T$, and zero otherwise. It is important to note that we do not allow the elective surgeries to be assigned to another OR, because each surgery has to be performed by the surgeon operating in the OR assigned to the surgery in the initial OR schedule. Thus, all elective surgeries have to be scheduled in the same OR as in the initial schedule. Because we only reschedule the not yet started surgeries, the start time of OR $j \in J$ for the rescheduling problem is either given by the start time of the OR in the morning or the expected end time of the last started surgery in this OR.

Within the rescheduling, it may be necessary to cancel an elective surgery, for example because of an arriving emergency surgery. The decision variable u_i denotes whether elective surgery $i \in I$ is canceled or not, i.e., the variable is one when the surgery is canceled and zero otherwise. When u_i is zero, the surgery is not canceled and therefore a new start time must be assigned, i.e., $\sum_{t\in T} s_{it}$ must be one in this case. When a surgery is canceled, the opposite holds, i.e., if $u_i = 1$ we must have $\sum_{t\in T} s_{it} = 0$. This is ensured by the following constraint.

$$\sum_{t\in T} s_{it} = 1 - u_i, \ \forall i \in I \tag{1}$$

The new start time of surgery $i \in I$ should fulfil a number of constraints. It should be greater than or equal to (i) the ready time of the patient which is given by Y_i, (ii) the start time of the assigned surgeon C_i which is given by D_{C_i}, and (iii) the start time of the assigned OR O_i. The following constraint ensures this.

$$s_{it} = 0, \qquad \forall i \in I, t < \max(S_{O_i}, Y_i, D_{C_i}) \tag{2}$$

The subset $I_{MD} \subset I$ denotes the set of surgeries that should start before a certain time because of medical reasons. This medical deadline of surgery $i \in I$ is given by L_i. Furthermore, it is not allowed to cancel these surgeries, i.e., we must have $u_i = 0$ and the surgery has to start before L_i.

$$\begin{aligned} &\sum_{t=0}^{L_i} s_{it} = 1, && \forall i \in I_{MD} \\ &u_i = 0, && \forall i \in I_{MD} \end{aligned} \tag{3}$$

The decision variable s_{it} and u_i completely determine the new OR schedule. However, to model the other restrictions and preferences some extra variables have to be defined which are introduced at the places where they are needed.

In each OR, only one surgery can be performed at a time. To model this, we need to determine if a surgery is ongoing at time $t \in T$. For this, we introduce the

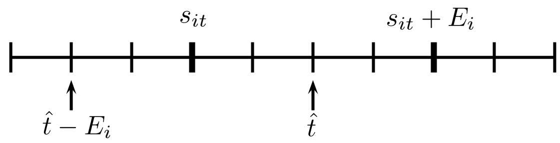


Fig. 2 Determine b_{it}

binary variables b_{it} which are one when surgery $i \in I$ is performed on time $t \in T$ and zero otherwise. A surgery is ongoing on time $t \in T$ when the start time of surgery $i \in I$ is between time t and time $t - E_i$. This is shown in Figure 2 and expressed by the following constraint.

$$b_{it} = \sum_{\hat{t}=t-E_i+1}^{t} s_{i\hat{t}}, \quad \forall i \in I, t \in T \tag{4}$$

The following constraint ensures that for each OR only one surgery can be performed at a time.

$$\sum_{i \in I_j} b_{it} \leq 1, \qquad \forall j \in J, t \in T \tag{5}$$

The above constraints describe some of the hard constraints for the rescheduling process resulting from the situation in the OR. In the following subsections, we describe and model the involved stakeholders. For each stakeholder, we describe the tasks the stakeholder has to perform during the day, the restrictions they impose on the OR schedule, the impact a change in the OR schedule has on the stakeholder and the preferences of the stakeholder. The impacts are modeled by linear constraints, and penalty costs for deviating from the preferences are incorporated in the objective function. The preferences of the stakeholders and the penalty costs are determined based on a questionnaire at the Isala Clinics (see Hartholt [9]).

2.1 Patient

The key stakeholder is the patient. For patients it is important that the surgery takes place at the scheduled time. Penalty costs are incurred when the new start time deviates from this preference. In order to determine the total penalty costs, we need to know the new start time of the surgery in the OR schedule. This time is denoted by the variable w_i, and in case surgery $i \in I$ is canceled, we define w_i to be equal to the start time of surgery $i \in I$ in the initial OR schedule.

$$w_i = \sum_t t s_{it} + u_i P_i, \; \forall i \in I \tag{6}$$

If we now denote by y_i the difference of the initial and new start time of surgery $i \in I$,

$$y_i = w_i - P_i, \qquad \forall i \in I \tag{7}$$

this variable y_i is zero when surgery $i \in I$ is canceled or when the start time of surgery $i \in I$ has not changed. The variable y_i is negative when surgery $i \in I$ starts earlier in the new OR schedule and when y_i is positive, surgery $i \in I$ starts later. As patients judge earliness and tardiness different, we split the variable y_i in two cases by introducing variables y_i^{later} and $y_i^{earlier}$. The variable y_i^{later} takes value y_i when y_i is positive, and variable $y_i^{earlier}$ takes value $-y_i$ when y_i is negative, which is ensured by the following constraints and the fact that the objective tries to minimize these variables.

$$\begin{array}{ll} y_i^{earlier} \geq P_i - w_i, & \forall i \in I \\ y_i^{earlier} \geq 0, & \forall i \in I \\ y_i^{later} \geq w_i - P_i, & \forall i \in I \\ y_i^{later} \geq 0, & \forall i \in I \end{array} \tag{8}$$

Based on the survey in the hospital, we concluded that patients assign different penalty costs to different values of y_i. To model this, a function $f_{PT}(y_i)$, denoting the penalty costs when surgery $i \in I$ is shifted y_i time periods, is introduced. This function is also split into two parts, namely $f_{PT}^{earlier}(y_i^{earlier})$ and $f_{PT}^{later}(y_i^{later})$.

Based on the patient survey, the penalty cost functions can be modeled best by step functions which are combinations of linear functions, see Figure 3. The specific value of the steps are also given by the questionnaire. To determine the correct value of the function $f_{PT}^{earlier}$ for a specific value of $y_i^{earlier}$, we introduce two parameters. The first is f_k, which denotes the function value in interval k, and the second is γ_k, which denotes the right endpoint of interval k.

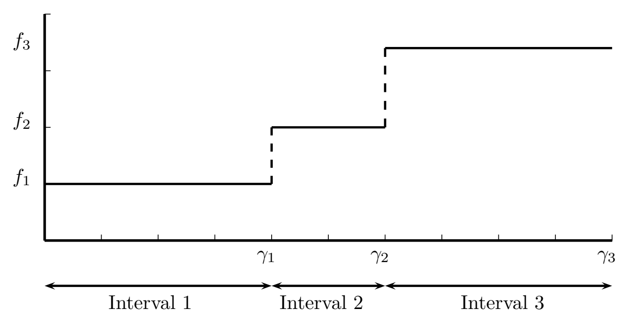


Fig. 3 Step function

To be able to incorporate these step functions in an ILP model, we introduce binary variables λ_{ik} which are one when $y_i^{earlier}$ is in interval k and zero otherwise. This is ensured by the following two constraints.

$$\begin{aligned} \sum_k \lambda_{ik}\gamma_k &\geq y_i^{earlier}, & \forall i \in I \\ \sum_k \lambda_{ik} &= 1, & \forall i \in I \end{aligned} \tag{9}$$

The value of the penalty function is now determined by:

$$f_{PT}^{earlier}(y_i^{earlier}) = \sum_k \lambda_{ik} f_k, \ \forall i \in I. \tag{10}$$

The total penalty costs of the patient group is given by p_{PT}, and is defined as the sum of the penalty costs of each patient.

$$p_{PT} = \sum_{i \in I} \left(f_{PT}^{earlier}(y_i^{earlier}) + f_{PT}^{later}(y_i^{later}) \right) \tag{11}$$

Because we minimize the total penalty costs, this method is only applicable for non-decreasing step functions.

2.2 Ward

Prior to surgery, the patient is admitted to a ward. On this ward, the patient is prepared for surgery. The survey showed that when a surgery starts earlier than scheduled, the workload on the ward increases if the patient is not ready yet. When a surgery starts later than scheduled, the workload can also increase. Therefore, penalty costs are incurred when there is a change in the start time of a surgery. The total penalty costs are calculated in the same way as for the patient. Based on the outcome of the survey a step function $f_W(y_i)$ is defined, which denotes the penalty costs for the wards if the start time of a surgery is shifted for y_i time periods. Note, that we do not distinguish between a surgery being scheduled earlier or later. The total penalty costs for wards is then given by $p_W = \sum_{i \in I} f_W(y_i)$.

2.3 Holding Department

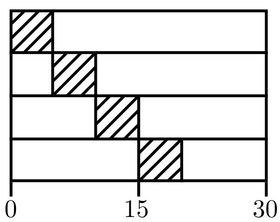
After the preparation on the ward, the patient is transported to the holding department where he/she is prepared further. The length of stay of patients on the holding department is given by V which can be longer than the preparation time needed. The holding department has a limited number of beds O_1 which provides a maximum for the number of patients treated at this department at the same time. Another limit on the number of patients who can be treated simultaneously is given by the available number of nurses at time $t \in T$ which is denoted by X_t. A nurse needs ρ minutes to prepare a patient, implying that X_t nurses can prepare at most $\frac{\delta}{\rho} X_t$ patients in time period t. Concluding, we define the capacity of the holding at time t by $\min\left(O_1, \frac{\delta}{\rho} X_t\right)$. The number of patients present on the holding on time $t \in T$ is denoted by l_t and is given by:

$$l_t = \textstyle\sum_{i \in I} \sum_{\hat{t}=t+1}^{t+V} s_{i\hat{t}}, \quad \forall t \in T \tag{12}$$

This number should be smaller than or equal to the capacity of the holding which is ensured by the following constraint.

$$l_t \leq \min\left(O_1, \tfrac{\delta}{\rho} X_t\right), \quad \forall t \in T \tag{13}$$

Note that when $\frac{\delta}{\rho} X_t \leq O_1$ for some $t \in T$, constraint (13) may exclude some feasible solutions (for an example, see Figure 4). If we want to prohibit this, we also need to schedule the preparation time of the patients. However, this increases the complexity of our problem. Note that this issue does not occur when the length of stay V equals δ which is the case for the instances used.



$V = 30$ minutes
$\rho = 5$ minutes
$\delta = 15$ minutes
$O_1 = 4$ beds
$X_t = 1$ nurse

Fig. 4 Excluded feasible solution

The survey at the Isala Clinics showed that the holding department prefers a levelled amount of patients that are present at each point of time. Therefore, penalty costs given by the step function $f_{HD}(l_t)$, are incurred when the number of patients l_t exceeds a certain threshold. The penalty costs for different values of l_t are specified by the staff of the holding department. As at the beginning of the day (until a prespecified time ψ), personnel from the recovery department assist on the holding department (no patients are present at the recovery department at this time), penalty costs are only incurred from time ψ on. The total penalty costs p_{HD} are given by $\sum_{t=\psi+1}^{T} f_{HD}(l_t)$.

2.4 Anesthetist

The anesthetist is responsible for administering and reversing anesthesia on one or more ORs. Therefore, he/she has to administer and reverse all anesthesias in these ORs. However, during the surgical procedure, the anesthetist does not have to be present in the OR. Therefore, similar to constraints (4) and (5), we include constraints which prohibits that more than one anesthesia is administered or reversed at a time in the ORs to which the anesthetist is assigned. For more details, see [9].

However, there are a few exceptions. When a surgery is complex, for example when the patient is younger than 6 months, the anesthetist must be present during the complete surgery which includes the surgical procedure. This means that during this time no anesthesia can be administered or reversed in one of the other assigned ORs. This is also ensured by constraints similar to constraint (5).

2.5 Surgeon

The surgeon is assigned to one OR and only has to perform the surgical procedure. This means that he/she does not have to be present during administering and reversing anesthesia. The constraints that ensure this are of the same structure as constraints (4) and (5).

2.6 OR Assistants

The OR assistants do not impose any restrictions on the OR schedule. Their only preference is that overtime is minimized. Overtime can occur because of arriving emergency surgeries and surgeries whose duration is longer than expected. Therefore, penalty costs are incurred when there is overtime. The amount of overtime in OR $j \in J$ is denoted by variable o_j. The value of this variable o_j is calculated by the following constraint.

$$o_j = \sum_{i \in I_j} \sum_{t=F_j+1}^{T} b_{it}, \ \forall j \in J \tag{14}$$

The step function $f_{OS}(o_j)$ provides the penalty costs for OR $j \in J$ when overtime of o_j time periods is incurred. The OR assistants specified the penalty costs for different values of o_j. The total penalty costs for the OR assistants is given by $p_{OS} = \sum_{j \in J} f_{OS}(o_j)$.

2.7 Recovery Department

After surgery, the patient is transported to the recovery department. Here, the patient is monitored while he/she recovers from surgery. The length of stay on this department varies with the expected duration of the surgery and is given by $\max(U, \frac{1}{2}E_i)$, where U is the minimum length of stay on this department. The number of patients present at the recovery department at time $t \in T$ is denoted by z_t and can be determined in the same way as for the holding department. The capacity of the recovery department is restricted by the number of beds O_2.

Another restriction is given by the number of patients who can be treated simultaneously, which depends on the number of available nurses R_t at time $t \in T$. Each nurse can monitor φ patients at a time, and therefore, φR_t patients can be treated simultaneously. Combining this with the number of beds O_2, the capacity of the recovery at time $t \in T$ is given by $\min(O_2, \varphi R_t)$. The number of patients present on the recovery department at time $t \in T$ should be less than or equal to this capacity. This is ensured by constraints that are of the same structure as constraints (5).

Like the holding department, the recovery department also prefers a levelled amount of patients that are present at each point of time. Therefore, penalty costs are incurred when the number of patients exceeds a certain threshold. This is modeled by the step function $f_{RC}(z_t)$ which provides the penalty costs incurred when z_t patients are present at time $t \in T$. The total penalty costs for the recovery is then given by $p_{RC} = \sum_{t \in T} f_{RC}(z_t)$.

2.8 Radiology Department

For some surgeries, an X-ray machine is needed during surgery. These surgeries are given by the set $I_{RL} \subseteq I$. For these surgeries a radiologist should be present during administering anesthesia and the surgical procedure. This means that he/she does not have to be present during reversing anesthesia. We restrict the number of required radiologist d_t at time $t \in T$ to be smaller than or equal to the number of available radiologists χ. The constraints that ensure this are similar to constraints (4) and (5).

The survey showed that it is important for the radiology department that their employees at the OR department finish as early as possible such that they can carry out other work at the radiology department. Therefore, penalty costs are incurred when a radiologist finishes later than needed, i.e., when the time the radiologists are present is longer than the time the radiologists are needed. In the following, we show how this is incorporated in the ILP when two radiologists are working in the OR. This method can easily be extended to the situation where more than two radiologists are available.

For each of the two radiologists, it has to be determined when their work is finished at the OR. These times are denoted by $\hat{d}_1$ and $\hat{d}_2$. The time the first radiologist finishes is equal to the latest time period both radiologists are needed. This is given by the following constraint.

$$\hat{d}_1 \geq t\,(d_t - 1)\,, \quad \forall t \in T \tag{15}$$

To determine the time the second radiologist finishes, we introduce binary variable $\tilde{d}_t$ which is one, when one or two radiologists are present on the OR at time $t \in T$. The value of this variable is given by the following constraints, where χ denotes the number of radiologists available during the day, in our case two.

$$\tilde{d}_t \geq \tfrac{d_t}{\chi}, \qquad \forall t \in T \tag{16}$$

The time the second radiologist finishes is now given by the latest time period that $\tilde{d}_t$ is equal to one.

$$\hat{d}_2 \geq t\tilde{d}_t, \qquad \forall t \in T \tag{17}$$

Using the above constraints and the fact that we minimize the working time of the radiologists, $\hat{d}_1$ and $\hat{d}_2$ denote the time the first and second radiologist finishes. However, this value does not equal the number of time periods they are actually present at the OR. To obtain this value, the start time and break time should be subtracted. The start time of the radiologists is given by $\min_j S_j$. All radiologists have a break of 45 minutes, i.e., $\frac{45}{\delta}$ time periods. The amount of periods the radiologists are having a break is thus given by $\upsilon = \frac{45\chi}{\delta}$. Therefore, the amount of time periods the radiologists are present at the OR is given by $\hat{d}_1 + \hat{d}_2 - \chi S_j - \upsilon$. This is an underestimation in case one or more radiologists finish before their break. However, we expect that this will rarely happen in practice.

The amount of time periods the radiologists are actually working at the OR is given by $\sum_{i \in I_{RL}} (E_i - Q_2)$, where Q_2 is the amount of time it takes to reverse anesthesia and E_i is the duration of surgery $i \in I_{RL}$. Now, the variable x defined by

$$x = 100 \left(\frac{\hat{d}_1 + \hat{d}_2 - \chi S_j - \upsilon}{\sum_{i \in I_{RL}} (E_i - Q_2) + 1} \right) \tag{18}$$

denotes the inverse of the fraction of time the radiologists are busy. The step function $f_{RL}(x)$ denotes the penalty costs incurred for a value of x, specified by the radiology department, and gives the total penalty costs p_{RL} incurred.

2.9 Pathology Department

During some surgeries, tissue is removed from a patient which needs to be examined by a pathologist. These surgeries are denoted by the set $I_{PA} \subseteq I$. After the surgical procedure, the tissue is transported from the OR to the pathology department. When tissue arrives after closing time, overtime is incurred. Let q_i be an integer variable which denotes the amount of overtime which would be created by a single surgery $i \in I$, i.e., the number of time periods the tissue arrives late plus the examination duration W.

As after closing time only one pathologist is available at the pathology department, the available pathologist has to successively process the tissues that arrive late. In most cases this means that the pathologists has to work $\sum\limits_{i \in I, q_i > 0} W$ periods in overtime. However, sometimes tissue will arrive so late, that the amount of overtime equals $\max_{i \in I} q_i$. Therefore, the amount of overtime q_{total} is estimated as follows:

$$q_{total} = \max \left(\max_{i \in I} q_i, \sum_{i \in I, q_i > 0} W \right) \tag{19}$$

When two sets of tissue arrive really late at approximately the same time, this number is a lowerbound on the amount of overtime. However, this situation is not likely to occur in practice.

Again, a step function $f_{PA}(q_{total})$ is used to express the penalty costs incurred for a value of q_{total} and represents the total penalty costs p_{PA} incurred for the pathology department.

2.10 Logistic Department

The logistic department is responsible for preparing materials needed during surgery. The materials are laid out in the order in which the surgeries are scheduled. When two surgeries are interchanged, the logistic assistant incurs penalty costs, because they have to change the order in which the materials are laid out. Two surgeries $i \in I$ and $\hat{i} \in I$ can only be interchanged when they are scheduled in the same OR, i.e., when $O_i = O_{\hat{i}}$. These two surgeries are interchanged when

$(P_i - P_{\hat{i}})(w_{\hat{i}} - w_i) > 0$, where P_i is the start time in the initial OR schedule and w_i is the start time in the new OR schedule. When this holds, we either have that both $(P_i - P_{\hat{i}})$ and $(w_{\hat{i}} - w_i)$ are positive or that both are negative. When both are positive, we have that $P_i > P_{\hat{i}}$ and $w_i < w_{\hat{i}}$. This means that in the initial OR schedule, surgery $i \in I$ was scheduled later than surgery $\hat{i} \in I$ and that in the new OR schedule, surgery $i \in I$ was scheduled earlier than surgery $\hat{i} \in I$. When both are negative, we have the opposite case.

We introduce binary variables $\kappa_{i\hat{i}}$ which are one when surgery $i \in I$ and $\hat{i} \in I$ are interchanged and zero otherwise. This is ensured by constraints (20), where T is the number of time periods per day. When $(P_i - P_{\hat{i}})(w_{\hat{i}} - w_i) > 0$, the variable $\kappa_{i\hat{i}}$ is set to one, however, when $(P_i - P_{\hat{i}})(w_{\hat{i}} - w_i) \leq 0$ the variable $\kappa_{i\hat{i}}$ could be set to either one or zero. But because we want to minimize the number of exchanged surgeries, the variable $\kappa_{i\hat{i}}$ gets the value zero.

$$(P_i - P_{\hat{i}})(w_{\hat{i}} - w_i) \leq T^2 \kappa_{i\hat{i}}, \forall (i > \hat{i}) \in I, O_i = O_{\hat{i}} \quad (20)$$

Let f_{LD} be the penalty cost incurred when two surgeries are interchanged, which value is specified by the logistic department. Then the total amount of penalty cost p_{LD} incurred for the logistic department is given by

$$p_{LD} = \sum_{j \in J} \sum_{(i,\hat{i}) \in I_j, i > \hat{i}} \kappa_{i\hat{i}} f_{LD}. \quad (21)$$

2.11 Objective Function

The goal of our model is to minimize the deviation from the preferences of the stakeholders. We denote the set of stakeholders by Π and we consider each stakeholder to be equally important. Since the order of magnitude of the cost functions introduced for the different stakeholders may differ, we have to introduce a weighted sum of the penalty costs p_π to compensate these differences. In this function, the priority β_π assigned to stakeholder $\pi \in \Pi$ is determined such that all stakeholders contribute approximately the same amount to the objective function value. The general concept of the weighted sum of penalties has furthermore the advantage that by varying the priorities, we can develop, for example, also a more patient centred OR schedule.

Next to the penalty costs for deviation from the preferences of stakeholders, we also include penalty costs η for canceling a surgery. These penalty costs are set such that they contribute more than the combined total penalty costs of the stakeholders in case surgeries are canceled. This way, it is clear that canceling a surgery is not preferred, however, if needed it is possible to do it. Summarizing, the objective function is given by

$$\min \sum_{\pi \in \Pi} \beta_\pi p_\pi + \sum_{i \in I} \eta u_i. \quad (22)$$

2.12 Problem Complexity

The problem introduced in the previous subsections has been modeled as an ILP. The following theorem justifies this approach, since it shows that efficient exact approaches are unlikely to exist.

Theorem 1 *The OR rescheduling problem is strongly NP-hard for two or more operating rooms.*

Proof We prove the theorem by reducing 3-partition to the OR rescheduling problem. The 3-partition problem can be formulated as follows. Given positive integers $a_1, \ldots, a_{3t}$, and b with $\sum_{j=1}^{3t} a_j = tb$, do there exist t pairwise disjoint subsets $R_k \subset \{1, \ldots, 3t\}$ such that $\sum_{j \in R_k} a_j = b$ for $k = 1, \ldots, t$? The 3-partition problem is proven to be strongly NP-hard (see Garey and Johnson [7]).

The reduction is based on the following transformation, where we set the priorities for the patient, ward, and the holding, recovery, radiology, pathology and logistic department to zero. Therefore, we only aim to minimize overtime and the number of cancellations. Furthermore, we consider 2 ORs which have their own anesthetist and $6t-2$ surgeries with the following processing times and ready times:

$$\begin{array}{lll} E_i = b, & Y_i = 0 & \forall 1 \leq i \leq t-1, i \in I_1, I_{RL}, \\ E_i = a_{i-t+1}, & Y_i = 0 & \forall t \leq i \leq 4t-1, i \in I_1, \\ E_i = b, & Y_i = 2b(i-4t) & \forall 4t \leq i \leq 5t-1, i \in I_2, I_{RL}, \\ E_i = b, & Y_i = b(i-(5t-1)) & \forall 5t \leq i \leq 6t-2, i \in I_2. \end{array}$$

The end and start times of the 2 ORs are:

$S_j = 0$, $F_j = (2t-1)b$ for $j \in J$.

The capacities of the holding and recovery departments are assumed to be larger than $6t-2$, thus we do not have to consider the given constraints for these departments. Furthermore, only one radiologist is available, and therefore, we have to consider the given constraints for the radiology department. Our goal is to create an OR schedule with objective value less than or equal to zero.

First note that, because of their ready times, the surgeries from $\{4t, 4t+1, \ldots, 6t-2\}$ in OR 2 have to be scheduled as in Figure 5 to achieve an objective value

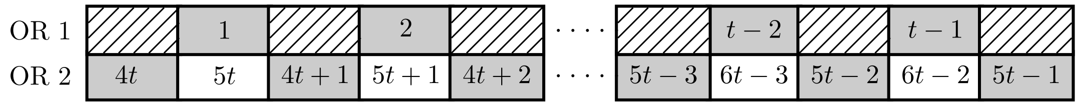


Fig. 5 Reduction of 3-partition problem to the OR Rescheduling problem

of zero, i.e., no overtime and cancellations may occur. In Figure 5, the grey blocks denote surgeries that need a radiologist and the white blocks denote surgeries that do not need a radiologist. Because the surgeries from $\{1, 2, \ldots t-1\}$ in OR 1 need a radiologist, they have to be scheduled in the time intervals where the radiologist is not busy in OR 2, i.e., as in Figure 5. This leaves us with t blocks of length b in OR 1 which have to be filled with the surgeries from $\{t, t+1, \ldots, 4t-1\}$ to achieve zero overtime with zero cancellations, and thus, an objective value of zero. Therefore, our problem has a solution with objective value zero if and only if there exists a solution to the 3-partition problem.

The proof of this theorem shows that already a very restricted version of the OR rescheduling problem is strongly NP-hard.

3 Computational Results

We tested our ILP on data from the Isala Clinics, a hospital in the Netherlands. The data consists of 1168 surgeries scheduled over 27 days. The surgeries consist of 354 emergency surgeries, 193 surgeries who need X-ray, 79 surgeries during which tissue is removed, and 7 complex surgeries. The average expected duration of the surgeries is 103 minutes, and the average realized duration of the surgeries is 91 minutes. Because rescheduling is only performed during working hours, we removed the emergency surgeries that start before 07:30 and after 18:00. We implemented our model in AIMMS 3.10 and solved it with CPLEX 12.1 on an AMD Ahtlon X2 Dual Core L310 1.2 GHz processor with 4 GB RAM.

In the first two subsections, we discuss the parameter settings for the ILP model and the achieved results which are used to derive the decision rules for the decision support system. In the last subsection, we determine the penalty costs for the initial OR schedule used at the Isala Clinics and the OR schedule realized at the end of the day. In addition, we optimize both the initial and realized OR schedule to show what improvements potentially can be realized when the developed method is used.

3.1 Parameter Settings

In this subsection, we discuss the parameter settings for the time periods and the priorities for each stakeholder.

To determine the appropriate length δ of the time periods, we solved the model for time periods of 5, 10, 15 and 20 minutes. We interrupted the ILP solver after 10 minutes of computation time. If after this time no optimal solution was found, we took the best solution found as our final solution. In Figure 6, the runtime for each combination of day and δ is given.

We would expect that a smaller value of δ would increase the runtime of our model. For most days in our instance this holds, however, in some cases, the runtime for our model with δ equal to 15 minutes is shorter than the runtime for our model with δ equal to 20 minutes. Furthermore, Figure 6 shows that for δ equal to 5 minutes, an optimal solution was only found for 2 of the 27 days. For δ equal to 10 and 20 minutes, this number increased to 13. The model with δ equal to 15 minutes performs the best, because an optimal solution was found for 15 of the 27 days. This result seems to be the consequence of the input data, since most of the data is given in multiples of 15 minutes, for example, the expected surgery duration and the length of stay on the holding department.

In Figure 7, we give the objective function value for each combination of δ and day. If solved to optimality, the objective value should increase when δ increases, because there is more flexibility in the OR schedule when δ is lower, i.e., the model with $\delta = 5$, should be able to provide the same or even a better solution than the model with δ set to 10, 15 or 20 minutes. However, Figure 7 shows that the worst objective values are achieved when δ equals 5. This is because for most days no optimal solution was found within 10 minutes. From Figure 7, we can conclude that our model with δ set to 15 minutes results in the lowest objective function value. Combining the results for the runtime and objective function, we choose to set δ to 15 minutes for further tests.

For each of the stakeholders, we have to determine its priority in the objective function. In the objective function, the total penalty costs of each stakeholder is multiplied by this priority. Our goal is that each stakeholder has approximately the same contribution in the objective function. In the following, we describe how we

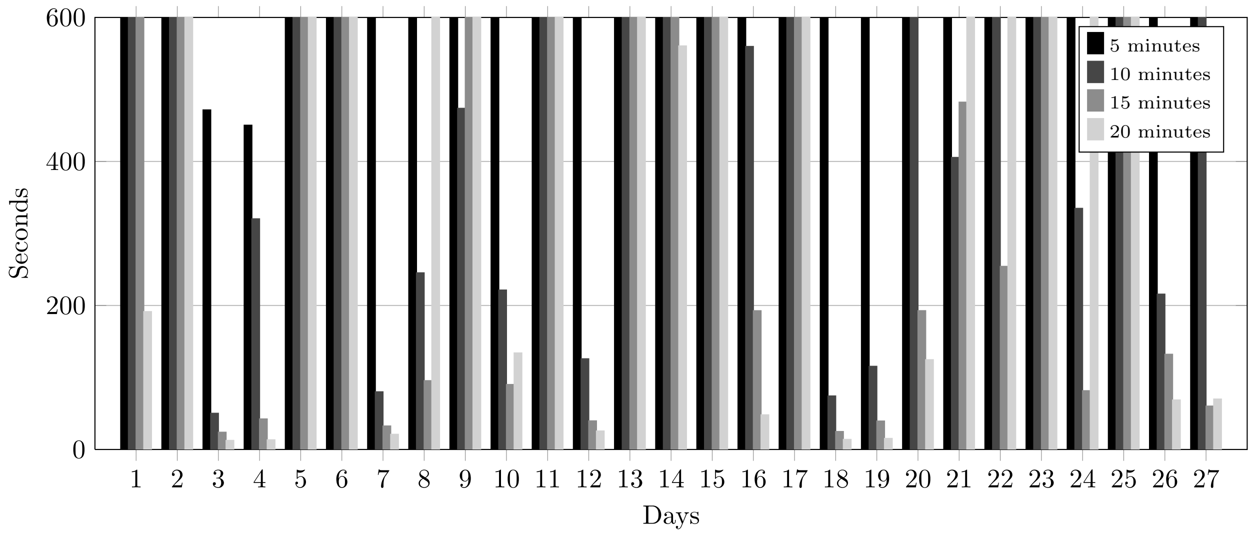


Fig. 6 Runtime for different values of δ

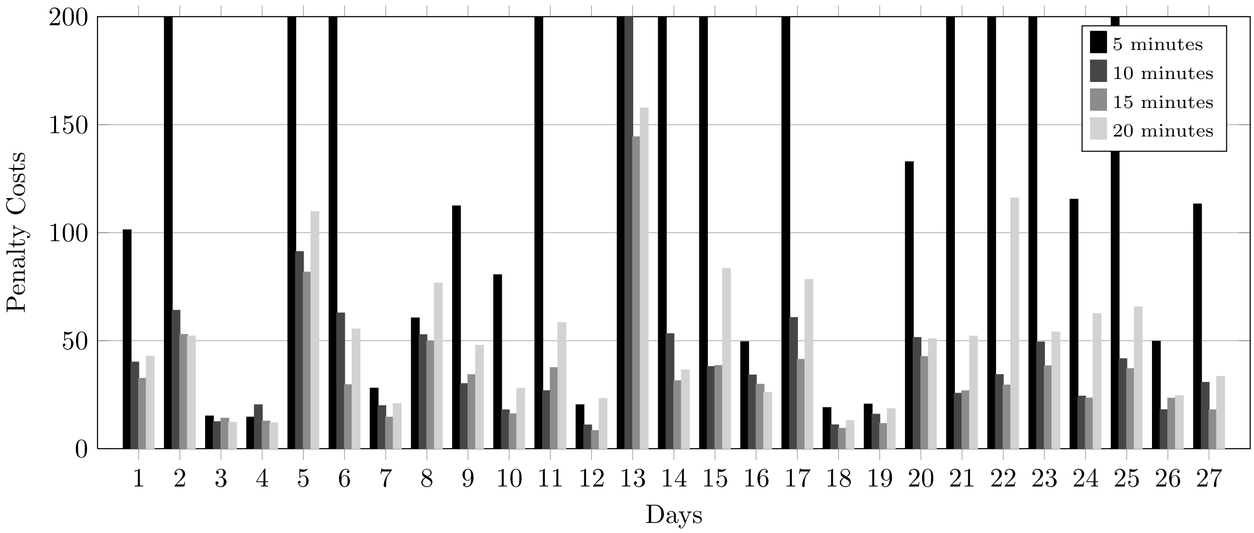


Fig. 7 Objective function value for different values of δ

have determined the priority of each of the stakeholders.

First, we solve our model where all stakeholders have priority one. Next, we adjust the priorities in such a way that the weighted cost of each of the stakeholders for the achieved solution is approximately the same. This is done by setting the priority of the stakeholder with the lowest total penalty costs to one and the priorities of the other stakeholders such that their weighted costs equals the lowest total penalty costs. Table 1 shows the results if this method is applied to our data, where the total penalty costs are the average total penalty costs incurred per day.

Note, that the holding department does not incur any penalty costs, because penalty costs are only incurred when four patients are treated simultaneously. The constraints imposed, however, limit the number of patients present on the holding department to three. This means that the holding department is not a bottleneck in the current situation.

We conducted some further tests where we varied these priorities slightly. The results from these tests show that patients, wards, and OR assistants have opposite interests compared to the recovery, radiology, pathology, and logistic department.

3.2 Deriving Decision Rules

The main goal of our model is to determine which adjustments to the initial OR schedule are allowed and preferred by the stakeholders. To determine this, we

Table 1 Total Penalty Costs and Priorities

	Patient	Ward	Holding	OR assistants	Recovery	Radiology	Pathology	Logistics
Total Penalty Costs	7.45	5.26	0.00	1.11	1.91	1.00	0.56	0.91
Priority	0.08	0.11	1.00	0.50	0.29	0.56	1.00	0.62
Weighted Costs	0.56	0.56	0.00	0.56	0.56	0.56	0.56	0.56

use our ILP model to create at three point $t \in T$ a new OR schedule which minimizes the deviation from the preferences of the stakeholders. For each of these three scenario's, the initial OR schedule is given as input as well as the realization of the duration of the surgeries that started before time t. These realized durations may change the initial OR schedule, because this schedule was based on the expected durations. Since we cannot change the OR schedule for the already started surgeries, we start rescheduling at the new start time S_j of OR j, which we define as the end time of the last started surgery before time t. In addition, we schedule not yet started emergency surgeries that arrived before time t. We assign a new start time s_{it} to each elective and emergency surgery that has not started at time t or, when allowed, cancel this surgery such that the resource constraints are fulfilled and the deviation from the preferences is minimized. The three scenario's are summarized below.

Scenario 1 After 10 a.m.: In this scenario, the realized durations of the surgery that started before 10 a.m. are known. An emergency surgery is only included if it arrived before 10 a.m..

Scenario 2 After 12 p.m.: In this scenario, the realized durations of the surgery that started before 12 p.m. are known. An emergency surgery is only included if it arrived before 12 p.m..

Scenario 3 After 2 p.m.: In this scenario, the realized durations of the surgery that started before 2 p.m. are known. An emergency surgery is only included if it arrived before 2 p.m..

These three scenario's are used to determine what adjustments our model makes to the OR schedule. For each of the scenario's, we determine how often one of the following adjustments occurred: (i) shifting a surgery, (ii) exchanging two surgeries, and (iii) canceling a surgery. In addition, we determine how often a break of a certain length was scheduled between two surgeries. The results are shown in Table 2.

Table 2 shows that shifting a surgery is the most frequent adjustment used, and often we see that a break

Table 2 Results Scenario 1, 2, and 3

	10 a.m.	12 p.m.	2 p.m.
Rescheduled surgeries	566	416	213
Shifted surgeries	375	297	176
Exchanged surgeries	1	0	0
Canceled surgeries	0	0	1
No break	264	183	71
Break 15 min.	166	112	66
Break 30 min.	62	33	21
Break 45 min.	22	19	11
Break > 45 min.	38	37	13
Mean break	15.84	18.71	19.78

is scheduled between two surgeries. The average length of a break is 15 to 20 minutes. When we only consider OR utilization, this may not seem to be optimal, however, these breaks can improve the perceived workload of other departments or may be necessary to fulfil the resource constraints. From the results we conclude that only two types of adjustments are preferred to be used. A surgery can be shifted or a break can be scheduled between two surgeries. This means that the order of surgeries stays the same during the day. So when we only allow these two adjustments, the number of feasible solutions decreases significantly, because we only have to consider one sequence of the surgeries instead of all possible sequences. This makes it possible to develop a simple heuristic to determine a good OR schedule. A further benefit of this is that we do not need an expensive ILP solver to implement our approach.

Based on this, we have incorporated this simple heuristic in a decision support system which is described in Section 4.

3.3 Potential Improvements

To determine what improvements the decision support system could potentially make compared to the OR schedules used at the Isala Clinics, we calculated, using the ILP model, the optimal initial OR schedule based

Table 3 Results Scenario 4 and 5

	Initial OR Schedule		Realized OR Schedule	
Total Penalty Costs	Original	Optimal	Original	Optimal
Cancellation	0.00	0.00	66.67	22.22
Patient	0.00	0.00	40.91	36.50
Ward	0.00	0.00	34.40	28.56
Holding	0.00	0.00	0.00	0.00
OR assistants	0.00	0.68	6.43	4.20
Recovery	4.93	0.74	8.85	3.11
Radiology	1.63	0.56	2.41	1.07
Pathology	0.64	0.15	0.70	0.51
Logistics	0.00	0.00	9.26	5.93
Total Costs	3.00	1.03	87.03	35.82

on the expected surgery durations. Note, that for this optimization the assignment of the surgeries to an OR is given as in the given initial OR schedule. Thus, we only change the sequences of the surgeries in each OR. None of the surgeries can be canceled, and because it is an initial OR schedule, the change in the start time of the surgeries is zero. This implies that the penalty costs for the patients, wards and logistic department are zero. Also, there are no emergency surgeries to be scheduled, because they have not arrived yet. This resulting fourth scenario is summarized below.

Scenario 4 Initial OR schedule: In this scenario, we compare the initial OR schedule used at the Isala Clinics with a new OR schedule determined by the ILP model, where we rescheduled all elective surgeries. Therefore, there are no emergency surgeries to be scheduled, and only the expected duration of each surgery is given.

We also optimized the realized OR schedule and compared it to the realized schedule provided by the Isala Clinics. For the realized OR schedule, all realized durations of the elective and emergency surgeries are considered to be known in advance, and also the canceled surgeries are taken into account. More precisely, we take as as input all elective surgeries with their realized duration that were planned in the initial OR schedule, and in addition, we include all performed emergency surgeries with their realized duration. For the canceled surgeries, we use the given expected surgery durations. For this scenario, it can happen that surgeries are canceled or that their start time changes, which results in penalty costs for patients, ward, and the logistic department. Note that the improvements made to the realized OR schedule can probably not be achieved in practice because not all relevant information is known beforehand. This fifth scenario is summarized below.

Scenario 5 Realization: This scenario consists of all the elective surgeries scheduled in the initial OR schedule and all emergency surgeries that arrived during the day. The realized duration of all surgeries is known.

Table 3 provides the average total penalty costs per day for each of the stakeholders and compares the initial and realized OR schedule of the Isala Clinics to the optimal OR schedules created by our ILP model. In the total costs, the priorities of the stakeholders are included.

Table 3 shows that in Scenario 4, the initial OR schedule, the total penalty costs for the recovery and radiology department decreases significantly. However, this can only be achieved by scheduling some surgeries in overtime. This follows from the slight increase of the total penalty costs for the OR assistants. For Scenario 5, the realization, the results show that the objective function value is reduced with more than 50%. The major decrease is caused by the reduction of the number of cancellations. Also, the total penalty costs for the recovery department decreases significantly. In practice, the penalty costs for the realized OR schedule will lay somewhere between 35.82 en 87.03 when the decision support system, discussed in the next section, is used.

Concluding, our model can potentially improve the initial and realized OR schedule significantly.

4 Decision Support System

To make our method applicable in practice, we have developed a decision support system which can be used

Stakeholder	Priority	Planning Penalty Costs	Planning Weighted Costs	Option 1 Penalty Costs	Option 1 Weighted Costs	Option 2 Penalty Costs	Option 2 Weighted Costs	Option 3 Penalty Costs	Option 3 Weighted Costs
Patient	0.05	26.20	1.31	25.90	1.26	26.20	1.31	26.20	1.31
Ward	0.08	26.60	2.13	25.20	2.07	26.60	2.13	26.60	2.13
Holding	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OR assistants	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.32
Recovery	0.16	13.00	2.08	11.00	1.76	13.00	2.08	13.00	2.08
Radiology	0.20	2.00	0.40	2.00	0.40	2.00	0.40	2.00	0.40
Pathology	0.10	0.70	0.07	0.70	0.07	0.70	0.07	0.70	0.07
Logistics	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total costs			**5.99**		**5.56**		**5.99**		**6.31**

Fig. 8 Decision Support System

by the OR manager. We incorporated the two decision rules that are derived from the results in Subsection 3.2. The first decision rule is that the order of surgeries must be maintained, but that a surgery can be shifted in time. In addition, the second decision rule states that it is allowed to schedule a break of at most one hour between two surgeries. This may help to decrease the perceived workload of several stakeholders and may be necessary to fulfil the resource constraints.

During the day, the OR schedule must be adjusted, because of arriving emergency surgeries and elective surgeries that take shorter or longer than expected. The user can indicate for which OR the schedule should be adjusted. The system evaluates, by means of complete enumeration, all possible solutions for this OR with respect to the two decisions rules. This means that between each two surgeries a break is scheduled with a duration that varies between 0 and 4 time periods. After all possible solutions are evaluated, the decision support system presents the three best options to the user. Only feasible solutions with respect to the constraints described in Section 2 are considered. A screenshot of the decision support system is shown in Figure 8. The first column of the screen-shot gives the specified priorities of all stakeholders. These values can be changed to create, for example, a patient centred OR schedule. The next column shows the penalty costs and weighted costs of the current OR schedule. The last three columns show the three best OR schedules with their penalty costs and weighted costs from which the user can choose.

The decision support system gives insight in how other departments are influenced by a change in the OR schedule by denoting the penalty costs and weighted costs incurred for each stakeholder. This can convince surgeons that it can be useful to schedule a break between two surgeries. In addition, the decision support system can determine whether the initial OR schedule is feasible or not by checking all constraints given in Section 2. The system denotes for each constraint how many times it is violated in the proposed OR schedule. It furthermore can be used to adjust the schedule such that it is feasible. Also, the penalty costs for the proposed OR schedule are calculated which gives an indication of how good the schedule is. The last advantage of the decision support system is that the realized OR schedule can be evaluated. This way, the OR manager can learn from his decisions made in the past.

5 Conclusions

In this paper, we formulated an ILP which determines the best adjusted OR schedule at a given point in time. The results show that patients, wards, and OR assistants have opposite interests compared to the recovery, radiology, pathology, and logistic department. Furthermore, the achieved results show that, without the few exceptions, the only used adjustments are (i) shifting surgeries, and (ii) scheduling breaks between two surgeries. These two decision rules are incorporated in the developed decision support system. This system determines the best adjusted schedule for one OR with respect to the given constraints and gives insight in how the workload of stakeholders is influenced by adjusting the OR schedule throughout the day. By using this decision support system, less surgeries are canceled and the perceived workload of all departments is reduced.

A drawback of the developed decision support system is that the decision rules may not be applicable when the priorities of the stakeholders change. A change in these priorities for the ILP can result in, for example, more exchanges or cancellations of surgeries. However, this is not expected in practice, because these two adjustments are less preferred than shifting a surgery.

Another drawback is that the decision support system can only improve the OR schedule for one OR at a time. This may result in a suboptimal solution. However, when the schedules of two or more ORs are improved simultaneously, the process of optimization may be unclear to the user and the acceptance of the achieved results may decrease.

Further research could focus on including the Central Sterile Supply Department (CSSD) into the model. This department prepares the instrument sets needed for a surgery. When a surgery is added to the OR schedule during the day, this may influence the workload on the CSSD. In addition, the CSSD may impose some extra constraints on the OR schedule.

There are several ways in which the developed decision support system can be used, for example, reschedule an OR immediately when it is disturbed or reschedule all ORs at some moments in time. The last example also raises the question in what order the ORs should be rescheduled. Therefore, it would be interesting to investigate the best way to use the decision support system.

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