Optimal Allocation of Operating Hours in Surgical Departments

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Abstract A large part of revenue in hospitals is generated in surgical departments. In order to use available resources efficiently, we propose an innovative tactical optimization model to optimally allocate operating hours for operating rooms. An extensive simulation study is applied to evaluate the tactical plan with respect to main stakeholders. Results indicate strongly positive effects on staff and patients.

1 Introduction

Surgical interventions ensure for a large part of revenue in every hospital [\[3](#page-6-0)]. Considering scarce resources, thorough planning is highly important, especially for operating rooms (ORs). That applies particularly in heart centers, since almost every patient needs surgical intervention. Most approaches in OR planning deal with scheduling strategies and assume given capacities [\[2,](#page-6-1) [5\]](#page-7-0). Other approaches aim at allocating the same total capacities differently to influence main performance criteria [\[6](#page-7-1)]. It is possible to use provided resources differently without further expenditure, resulting in the same total capacity but different resource allocation. In close cooperation with a hospital for thoracic and cardiovascular surgery, we aim at determining optimal allocation of operation hours among ORs on a tactical level. Total operating time over all ORs is defined by available resources such as staff, equipment and legal regulations. We propose an innovative optimization model to optimally allocate operating hours. This tactical solution is evaluated using an extensive simulation study. Optimal allocation of total operating time with regard to different ORs and patients' requirements is able to positively affect staff and patients.

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2 Optimal Allocation of Operating Hours

In this chapter, we propose an optimization model for optimal allocation of operating hours. In hospitals, patients have different medical requirements and the ORs are differently equipped. Therefore, not every patient type can be treated in every OR. Furthermore, patient types are differentiated into patient groups according to their expected surgery duration. Depending on the specific hospital, the share of patients of each group varies considerably resulting in a hospital-specific case mix which is almost constant in the medium term. Since the demand for types of ORs varies dependent on the case mix, operating hours of the ORs need to match it. The following linear stochastic optimization model decides on daily operating hours for every OR on a tactical level which are valid for every day in the planning horizon.

On an operational level, the throughput of patients is an important performance criterion. For our medium term consideration, we take the number of patients to treat per day as given, to focus on the impact of operating hours. Another important criterion for hospital performance is employee satisfaction which needs to be high to guarantee best possible patient care. Hence, the objective is to minimize overtime as an indicator for staff satisfaction. Similar to common approaches to consider uncertainty in constraints, our model computes worst-case overtime. Taking the 95th percentile, the tactical model guarantees for a high probability of minimum overtime. Our tactical linear stochastic optimization model decides mainly on operating hours c_j in minutes for each specific OR $j \in \mathcal{J}$. Besides, patients are assigned to ORs depending on their medical group $l \in \mathcal{L}$ with the variable x_{il} . Since we decide on a tactical level, all patients admitted must be assigned to an OR. Variation and uncertainty in the number of patients and type are represented through scenarios and reflect the hospital's case mix. Every scenario is weighted depending on the occurrence in the hospital's case mix with the parameter w^s . The objective is to minimize the expected sum of overtime minutes (o_j^{s+}) over all ORs $j \in \mathcal{J}$ and scenarios $s \in \mathcal{S}$ (see (1)).

$$
\min \sum_{s \in \mathscr{S}} \sum_{j \in \mathscr{J}} w^s \cdot o_j^{s+} \tag{1}
$$

The model considers that the overall OR time *C* per day remains constant and that in each scenario each patient is assigned to an OR (see $(2-3)$ $(2-3)$). c_i decides on the capacity of OR $j \in \mathcal{J}$ in minutes, while b_i^s is the number of patients of group $l \in \mathcal{L}$ to be scheduled in scenario $s \in \mathcal{S}$. x_{jl}^s decides on the number of patients of group $l \in \mathcal{L}$ to be treated in room $j \in \mathcal{J}$ in scenario $s \in \mathcal{S}$.

$$
\sum_{j \in \mathcal{J}} c_j = C \tag{2}
$$

$$
\sum_{j \in \mathscr{J}}^s x_{jl}^s = b_l^s \qquad \qquad \forall l \in \mathscr{L}, s \in \mathscr{S} \tag{3}
$$

Only one optimal allocation of operating hours for all scenarios is allowed and over- and undertime $(o_j^{s+}$ or o_j^{s-} , respectively) are calculated through a worst-case assumption—every group's surgery duration is expected to be as long as the 95th percentile $a_l^{0.95}$ derived from historical data (see [\(4\)](#page-2-0)).

$$
\sum_{l \in \mathcal{L}} x_{jl}^s \cdot a_l^{0.95} + o_j^{s-} - o_j^{s+} = c_j \qquad \forall j \in \mathcal{J}, s \in \mathcal{S} \qquad (4)
$$

Moreover, it ensures that the assignments meet the requirements for every patient type (see [\(5\)](#page-2-1) and Fig. [1\)](#page-3-0). $\mathscr A$ is the set of patient groups with special requirements, and Eq. [\(5\)](#page-2-1) prevents them from being assigned to an unsuitable OR.

$$
\sum_{l \in \mathcal{L}_a} \sum_{j \in \mathcal{J} \setminus \mathcal{J}_a} x_{jl}^s = 0 \qquad \forall s \in \mathcal{S}, a \in \mathcal{A}
$$
 (5)

Finally, domain constraints ensure that $c_j \in \mathbb{N}_0$, $x_{jl}^s \in \mathbb{N}_0$ and o_j^{s+} , $o_j^{s-} \ge 0$. c_j is limited to an interval $\mathscr C$ defining minimal and maximal operating hours for the ORs. Since the operating hours are determined based on the considered scenarios, it is of high importance that these match the hospital's case mix. For computational reasons, it is not possible to include all information of daily patient occurrence provided by a hospital into the optimization model, instead, we use scenario reduction as in Heitsch and Römisch [\[4](#page-7-2)]. The Euclidean distance weighted inversely proportional with the average number of patients per week per group acts as a measure for the distance between two scenarios. The weighting parameter w^s is the share of scenarios best represented by scenario $s \in \mathcal{S}$. Implementation for heart centers is exemplarily shown in the next section.

3 Case Study

Data Analysis

This case study is based on data collected in a large hospital for thoracic and cardiovascular surgery in Germany. We include detailed data of more than 40,000 surgeries performed between 2009 and 2015. The patient collective consists of children patients, hybrid patients, who need combined cardiological and cardiothoracic interventions, and the remaining patients with no special requirements for the equipment of their OR (regular patients). These three patient types are additionally subdivided into nine patient groups according to their expected surgery duration (without emergencies). Figure [1](#page-3-0) shows feasible assignments from patient groups to eight available ORs. There are three different types of ORs matching the patient types. Rooms one to six have no special equipment, room seven is a hybrid OR and room eight fits children's requirements. The total available OR time per day, *C* = 5*,*340 min, is allocated among the ORs and each room starts at 7:45 a.m. For every patient group (including

Fig. 1 Feasible assignments of patient groups to ORs

emergency patients), distribution functions for the surgery duration and the number of patients per week are calculated, which fit realistic data (see Table [1\)](#page-4-0).

Strategies for Resource Allocation

The optimization model introduced in Sect. [2](#page-1-3) computes optimal operating hours for the ORs. Using scenario reduction, 1,705 scenarios are reduced to ten best representing all remaining and thus representing the hospital's case mix. With this drastically reduced number of scenarios, information from 1,705 scenarios is aggregated in the weights and shapes of the remaining ten scenarios.

Figure [2](#page-5-0) shows different alternatives for operating hours. Alternative *OPT* is the result of the optimization model, we compare it with the current real-world situation (Alternative *R*) and with uniform operating hours (Alternative *U*).

Evaluation

These three different alternatives are tested in a simulation study using our evaluation tool which simulates the workflow in the ORs (see Fig. [3\)](#page-5-1). For each alternative, the corresponding operating hours are fixed for the whole investigation period. We measure the quality of the optimal results threefold with regard to three main stakeholders. Apart from the staff, we consider patients and management. On patient side, we study postponement of patients (actual treatment day \neq planned treatment day). For management requirements we consider the OR utilization and on employee and especially physician side, we focus on the amount of overtime. Operational OR planning is often divided into two steps repeated daily or weekly. The first step plans the admission of patients for the upcoming week. Afterwards, the exact order of the surgeries is determined every day. Our evaluation tool is a framework that connects these planning steps by using the output of one step as the input for the following one. Each planning step is supported by hospital manager's rules. For example, children patients are preferably treated in the morning and patients whose appointments have been postponed from the day before are considered with higher priority in the next step to avoid further postponement. These daily schedules are included in our simulation model. The number of patients per week as well as the surgery duration for the patients is generated through probability distributions fitting realistic data and are considered according to Table [1.](#page-4-0) Moreover, the interarrival times of emergencies in minutes are exponentially distributed ($\lambda = 420$) to generate 24 emergencies per week on average. We evaluate 52 weeks, that is 52 runs of weekly admission planning

Fig. 2 Alternatives for allocation of operating hours

Fig. 3 Operational evaluation framework (Alternatives as in Fig. [2\)](#page-5-0)

and 260 runs of daily allocation planning. During the year, we have approximately 5,400 patients undergoing surgery.

Results

Modified operating hours influence three main characteristics corresponding to the three main stakeholders in hospitals. Referring to staff interests, overtime should be avoided. Evaluation shows significant improvement in the daily amount of overtime over the whole period investigated. The 95th percentile of daily overtime—which is the sum of overtime minutes across all ORs—is 716.3 min for *R*, 785.8 min for *U* and only 557.6 min for *OPT*. As shown in the boxplots (Fig. [4\)](#page-6-2), best results are achieved in *OPT*, while *U* performs considerably worse. *R* shows similar results to *OPT*, but each value, especially the median, is higher. Not only the staff, but also the patients benefit from an optimal resource allocation. *OPT* performs considerably better than *U* and *R*. In *OPT* we have the highest share of patients being treated on the assigned day (94%). Compared to \mathbb{R} (91% treated on the assigned day) the share of patients being postponed decreased by three percentage points (∼150 patients/year) using alternative *OPT*. With 11% of postponed patients *U* performs worst. Although in general the stakeholder's interests are conflicting, our optimal solution supports the management's interests as well. As seen in Fig. [5,](#page-6-3) improving the working condition for the staff and patients' interests does not negatively affect the OR utilization or the number of patients being treated.

4 Conclusion

Using the innovative optimization model, staff overtime and patients rescheduling is considerably reduced. Reallocation of operating hours in ORs can promote main stakeholder's interests in a hospital. Variation of operating hours impacts shift planning and scheduling. Following the current development to flexible shift models in order to reconcile family and career, new operating hour schedules can be integrated to avoid unplanned overtime [\[1\]](#page-6-4). Further research on the optimal allocation of operating hours to investigate the interaction between over- and underestimation of surgery duration could additionally improve the performance of OR utilization.

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