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Innovative Applications of O.R.

Solution methods for the tray optimization problem

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ABSTRACT

In order to perform medical surgeries, hospitals keep large inventories of surgical instruments. These instruments need to be sterilized before each surgery. Typically the instruments are kept in trays. Multiple trays may be required for a single surgery, while a single tray may contain instruments that are required for multiple surgical procedures. The tray optimization problem (TOP) consists of three main decisions: (i) the assignment of instruments to trays, (ii) the assignment of trays to surgeries, and (iii) the number of trays to keep in inventory. The TOP decisions have to be made such that total operating costs are minimized and such that for every surgery sufficient instruments are available. This paper presents and evaluates several exact and heuristic solution methods for the TOP. We compare solution methods on computation time and solution quality. Moreover, we conduct simulations to evaluate the performance of the solutions in the long run. The novel methods that are provided are the first methods that are capable of solving instances of realistic size. The most promising method consists of a highly scalable advanced greedy algorithm. Our results indicate that the outcomes of this method are, on average, very close to the outcomes of the other methods investigated, while it may be easily applied by (large) hospitals. The findings are robust with respect to fluctuations in long term OR schedules.

1. Introduction

Throughout the developed world, health care costs have shown a tremendous increase over the last decades. Since 1970 the inflation adjusted government spending on health care has risen by nearly 5% per year (Hagist & Kotlikoff, 2005), currently averaging 9% of gross domestic product (OECD, 2014). At the same time, patient waiting lists have become longer and are nowadays a major problem (Worthington, 1991). Managerial efforts to control the steeply rising health care costs and long patient waiting lists have not only placed attention on main health care processes, but have focused especially on efficiency management of various, priorly neglected, side processes. One such side process which has received recent attention is hospital sterilization logistics.

Hospital sterilization logistics is a relatively large side process in the hospital sector. Hospitals in developed countries typically have invested millions of euros in sterile instruments used for surgeries and other procedures. Optimizing the logistic design of the sterilization processes can free substantial amounts of money and working capital. It is estimated that in a small country such as the Netherlands, the saving potential is well over 100 million euros (van de Klundert, Muls, & Schadd, 2008). Moreover, the optimization of the sterilization logistics can lead to increased throughput, allowing more patients to be helped in a fixed time frame. This can help reduce patient waiting lists and reduce opportunity cost of health care which is currently not provided.

In this paper, we focus on the inventory management of sterile instruments. These sterile instruments flow in a return cycle between the central sterilization department (CSD) and for instance the operating theater. The sterile instruments are mostly grouped in special trays. Such a tray can contain the items needed for a particular surgery, but it can also happen that the content of a tray is needed for several types of surgery, or that one type of surgery requires multiple trays of different types. Hospitals face three questions regarding the management of instrument trays: (i) how many trays of each type should be obtained, (ii) how should the tray types be composed, and (iii) how should the tray types be assigned to surgeries? The problem of optimizing the tray composition is called the *tray optimization problem* (TOP).

The first two questions of the TOP are interlinked: the number of required trays and instruments depends largely on the composition of the trays. Optimizing the composition of trays can lead to substantial cost savings and to increased availability of instruments, see van de Klundert et al. (2008). In this research,

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we investigate ways for solving the TOP to minimize cost whilst guaranteeing instrument availability.

Substantial savings can already be achieved by removing unused instruments from the existing trays. The contents of a tray develop historically as new surgeons place additional instruments on a tray while the instruments used by retired surgeons remain on the tray. In addition, surgeons may prefer different instruments for the same surgery which increases the inventory and sterilization costs. By reaching consensus on which instruments to use for each surgery type, substantial savings can be made.

As mentioned, even higher cost savings can be achieved by composing the trays from scratch by solving the TOP. Currently, only few papers consider this tray optimization problem. Van de Klundert et al. (2008) present an Integer Linear Program (ILP) to solve the TOP. However, the authors also prove that the TOP is NP-hard, and therefore, no solution is guaranteed within polynomial time.

Reymondon, Pellet, and Marcon (2008) introduce a Simulated Annealing (SA) approach to solve the TOP. As the computation time for the presented SA approach is still extremely long for realistic instance sizes, they also introduce a simpler heuristic. This heuristic starts with two extreme solutions, namely (i) one tray for each instrument, and (ii) one tray for each surgery type. For both extreme solutions, the cost per instrument is calculated. If it is cheaper to individually wrap an instrument, this particular instrument is removed from the trays in the second extreme solution. A next step would be to distribute the individually wrapped instruments over the created trays to further reduce costs. However, this step is not yet implemented.

The contribution of this paper is threefold. First, we give an overview of the existing models and solution approaches for the TOP. Second, we present three new solution methodologies. The first one is based on delayed row & column generation (Muter, Birbil, & Bülbül, 2013), the second is a greedy heuristic, and the third is a genetic algorithm. Third, we compare the new solution methodologies to the existing approaches on several problem instances derived from real-world data sets. We perform numerical experiments to assess both the quality and the computation time of the solution approaches.

A key aspect of the TOP is that the composition of the trays and the assignment of trays to surgeries is considered simultaneously. A similar structure is observed in many other applications as well. For example, consider a workforce consisting of employees with different skill sets. A number of tasks is given that all require a set of skills and have to be performed by a group of employees. In order to be able to manage the workforce smoothly, the employees are distributed over teams. Then, the teams are assigned to the tasks. In this assignment, it must be ensured that the employees in a team have the required skills for the tasks the team is assigned to. The approaches described in this paper can be applied to this problem as well.

This paper is structured as follows. In Section 2, we formally introduce the problem. In addition, we describe several variants for the objective function and capacity constraints. In Section 3, several exact and heuristic solution approaches are described. A simulation approach to compare the developed solution approaches in a realistic setting is introduced in Section 4. In Section 5, we describe and analyze the computational results for the introduced solution methods and their performance in the simulation study. Section 6 presents conclusions and gives recommendations for future research.

2. Problem formulation

The basis of the considered problem is creating instrument trays and assigning these instrument trays to surgeries. The instrument trays are created by assigning several instruments to a tray while respecting some capacity constraints which are described in Section 2.1. The created instrument trays are assigned to surgeries such that for each surgery the required instruments are available in the assigned instrument trays. The set of instruments is given by set I, the set of surgeries by set J, and the set of instrument trays by set K. Integer variable X_{ik} denotes the amount of instruments $i \in I$ assigned to instrument tray $k \in K$. Integer variable Y_{jk} indicates how many instrument trays of type $k \in K$ are assigned to surgery $j \in J$. For each surgery $j \in J$, the number of instruments of type $i \in I$ needed to perform this surgery is given by parameter d_{ij}. Then, the following constraint ensures that at least d_{ij} instruments of type $i \in I$ are available in the instrument trays $k \in K$ assigned to surgery $j \in J$.

$$\sum_{k \in K} X_{ik} Y_{jk} \geq d_{ij}, \quad \forall i \in I, j \in J. \tag{1}$$

Note that this constraint is non-linear, however, it can be easily linearized as shown in Section 3.

2.1. Capacity restrictions

As mentioned, the created instrument trays must respect some capacity constraints. Normally, a tray has a restriction on the weight and volume it can contain. To specify the restrictions on the total weight and volume a tray can contain, we introduce α_i and β_i as the volume and weight of instrument $i \in I$, respectively. The maximum allowed weight and volume on a tray is given by r_α and r_β, respectively. This leads to the following two constraints.

$$\sum_{i \in I} \alpha_i X_{ik} \leq r_\alpha, \quad \forall k \in K, \tag{2}$$

$$\sum_{i \in I} \beta_i X_{ik} \leq r_\beta, \quad \forall k \in K. \tag{3}$$

However, in practice, the weight and volume of the instruments may not be available. Therefore, an alternative is to limit the number of instruments that can be placed on a certain tray. This can be done with the following constraint, where r_γ represents the maximum number of instruments allowed on a tray.

$$\sum_{i \in I} X_{ik} \leq r_\gamma, \quad \forall k \in K. \tag{4}$$

These three constraints can also be summarized into the following constraint:

$$\sum_{i \in I} p_i^n X_{ik} \leq r^n, \quad \forall k \in K, n \in N, \tag{5}$$

where $N = \{1, 2, 3\}$ is the set of characteristics of the instruments and trays. In particular, $p_i^1 = \alpha_i,\ p_i^2 = \beta_i,\ p_i^3 = 1,\ r^1 = r_\alpha,\ r^2 = r_\beta$ and $r^3 = r_\gamma$.

Note that it is preferred to consider the weight and volume of the instruments when filling the instrument trays. This information should in general be known by the manufacturer, but in case this information is not available, Constraint (4) can be used.

2.2. Objective function

The preferred assignment made by variables X_{ik} and Y_{jk} is the one that minimizes the total incurred costs. These costs can be divided into several parts, namely:

- fixed periodic costs,
- sterilization costs,
- handling costs,
- costs for new tray type.