A method for clustering surgical cases to allow master surgical scheduling

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Abstract

Master surgical scheduling can improve manageability and efficiency of operating room departments. This approach cyclically executes a master surgical schedule of surgery types. These surgery types need to be constructed with low variability to be efficient. Each surgery type is scheduled based upon its frequency per cycle. Surgery types that cannot be scheduled repetitively are put together in so-called dummy surgeries. Narrow defined surgery types, with low variability, lead to a large volume of such dummy surgeries that reduce the benefits of a master surgical scheduling approach. In this paper we propose a method, based on Ward's hierarchical cluster method, to obtain surgery types that minimizes the weighted sum of the dummy surgery volume and the variability in resource demand of surgery types. The resulting surgery types (clusters) are thus based on logical features and can be used in master surgical scheduling. The approach is successfully tested on a case study in a regional hospital.

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1 Introduction

Hospitals are complex-structured organizations that are often hard to manage (5; 4). An operating room department is a typical example of a department where many different actors cooperate, which leads to a complex organizational situation. Moreover, hospitals consider operating room departments as the organization part that generates the most revenue and the most costs. Hence, manageability and the efficiency of this department is subject of a broad range of studies, see for examples (7; 1; 15). A good overview of operating room planning and scheduling can be found in Cardoen *et al.* (2) and McIntosh *et al.* (10).

One approach to improve efficiency and manageability of operating room departments is the so-called master surgical scheduling approach (8; 13; 12). It cyclically executes a master surgical schedule (MSS) of surgery types. An MSS allows not only for optimization of operating room utilization, robustness, and overtime, but it also takes resource demand on other departments such as wards into account. The surgery types in an MSS function as its building blocks. Based on their resource demand profiles the MSS is optimized (13; 12). Constructing surgery types with little variability in their resource demand is therefore preferred.

Newly arrived patients or patients from waiting lists are assigned to surgery types in an MSS on a weekly basis. To reduce the probability of non-assigned surgery types, the historical frequencies of the demand for a surgery types per week are rounded down to obtain the frequencies of surgery types that are allocated in the MSS. For example, when cataract surgery occurs on average 6.7 times per week, only 6 surgeries of the cataract type are incorporated in the MSS. The remaining demand fraction will be allocated in so-called dummy surgery types. The positive effect of using an MSS is reduced when the volume of dummy surgeries becomes large. We therefore aim to construct a set of surgery types with a low volume of dummy surgeries as well as a low variability in demand usage.

In this paper we propose a method to obtain such a set of surgery types. We draw more elaborately the background of the problem in Section 2 and we formally introduce the problem in Section 3. In Section 4 we provide a brief summary of available method for clustering. Our suggested solution approach is presented in Section 5 and applied to a case study in Section 6. We conclude the paper in Section 7.

2 Problem context

An MSS is built from a set of recurrent surgery types. The problem at hand is to create a limited number of logistically and medically homogeneous surgery types. Examples of logistical characteristics are length of stay and surgery duration; examples of medical characteristics are diagnosis related groups and procedure codes. We assume that a previous period is representative for the coming period, both for the frequency of occurrence of surgical cases as for the variability in resource consumption by patients.

We focus in this research on the construction of surgery types for the elective case mix. Aside from the standard surgery types for elective care, additional types can be defined to cover the emergency and semi-urgent case mix. The hospital organization may impose restrictions on the surgery type clustering. For instance, clustering might be done only within a surgical department as we assume in this paper.

The frequencies of surgery types are calculated as follows. Given historical data, surgery types are constructed as combination of one or more specific surgical cases. The surgical cases define the lowest level in the required data. Given a surgery type, and the historical demand for its underlying surgical cases, an average frequency per MSS cycle is calculated. Management may require that the MSS cycle length is aligned with other process cycles in the hospital such as personnel rostering. Furthermore a hospital may not be opened during all weeks. After obtaining an average frequency per MSS cycle, given its length and the total number of repetitions per year, the frequency is rounded down. The remaining fractions of surgery types are clustered into dummy surgery types. Clearly the volume of dummy surgery types depends on the definition of the surgery types. When a set consists of surgery types that are broadly defined, this tends to reduce the volume of dummy surgery types, but lead to higher uncertainty in the resource consumption of patients assigned to such a broadly defined surgery types than a situation where patients are assigned to narrowly defined surgery types. However, the latter may results in a substantial volume of dummy surgery types which is conflicting with the MSS approach. Ideally, only a small proportion of the case mix is covered by dummy surgery types.

An MSS aggregates the level of surgical scheduling from individual patients to patient types. The loss of information due to this aggregation (e.g., surgery duration will be less predictive) will be compensated by benefits inherent to the MSS approach (12). Still, when constructing surgery types, we aim to minimize the loss of information in the process of constructing surgery types.

3 Problem definition

We denote Z as the set of all surgical cases that are performed in the hospital by a surgical department, with $z \in Z$ a particular surgical case. Let us consider a hospital that wants to optimize utilization of resources $r = 1, \ldots, R$ by means of an MSS. These resources may vary in importance, for instance by their costs, we therefore scale the different resources r by parameter w_r.

We perform the clustering of surgical cases based upon patient data of the previous period, hence we use post-classification. For reasons of simplicity we assume that this period equals one year. Let I be the set of all patients that are operated in that year. We denote their consumption of resource r, scaled by w_r, for patient i by X_{ir}.

Let $c \in C$ be a particular surgery type. We introduce subset I^z to denote all patients that were admitted for surgical case z. Subset Z^c denote the surgical cases z that are clustered to surgery type c. The MSS approach requires that all surgical cases are assigned to exactly one surgery type, therefore $Z^c \cap Z^{\bar{c}} = \emptyset$ for $c \neq \bar{c}$ and $\sum_{c \in C} Z^c = Z$.

Our problem now comprises of optimizing the clustering of surgical cases z in surgery types c such that the weighted sum of the volume of dummy surgeries and the variability within clusters is minimal. This way we obtain logistically homogeneous clusters usable in an MSS. Clustering might be subject to additional constraints, as in our case surgery types are constructed per surgical department.

4 Literature

Clustering problems and cluster analysis form a large research area. Also in the area of health care this topic is far from new. An excellent overview of existing techniques and their application in a health care setting is given by Dilts *et al.* (3). The complexity of clustering problems rapidly increases with the problem size (9). Therefore solution algorithms are often derived from available methods in the field of mathematical programming, see for example Hansen and Jaumard (6).

Algorithms to solve clustering problems are usually subdivided into hierarchical algorithms and non-hierarchical algorithms (e.g., partitioning algorithms) (3; 9). Constraints may be added to hierarchical methods to reduce the number of possible splits or merges. The optimal number of clusters does not need to be known beforehand. An investigator selects the best set of clusters after all different number of clusters are generated. Hierarchical cluster algorithms are either agglomerative or divisive in nature. Agglomerative hierarchical methods successively combine items closest to one another into a new cluster until one cluster is left. Divisive methods start with all items grouped in one cluster, and successively split off a set of items to form a new cluster. The divisive splitting is based on either one variable (monothetic) or upon multiple variables (polythethic).

Non-hierarchical methods generally start with an initial set of clusters. Based upon the definition of similarity/distance measure items are assigned to these clusters by some heuristic. Afterwards items may be reassigned to further optimize the clustering. The K-means method is one of the well known methods in this group of cluster algorithms. For a detailed overview of available clustering techniques and their application we refer to Dilts *et al.*(3), Romesburg (11), and Johnson and Wichern (9).

The need to classify patients to allow advanced planning and scheduling has also been acknowledged in the field of health care logistics, see for example Vissers *et al.*(14). They show in their paper how classification of patients can be used to improve hospital management using patient clustering as one of their building block in a logistical framework. Manuster *et al.* show the application of clustering techniques to obtain logistic-based patient groups of patients treated for peripheral arterial vascular diseases. The authors show that the resulting clusters support improved planning and control of patients to increase the efficiency of resources within hospitals.

In our problem, as addressed in Section 1, the volume of dummy surgeries negatively influences the performance of an MSS. A large number of clusters/surgery types tends to lead to a high volume of dummy surgeries. Basically this makes that the number of surgery types cannot be determined in advance. Therefore hierarchical cluster methods fit our problem better than non-hierarchical methods do. Furthermore, from a mathematical point of view the cost of the volume of dummy surgeries can be described by a step-wise cost function on the number of items in the clusters. To the best of our our knowledge no other papers have been published that use such costs function in the context of clustering problems.

We aim to construct surgery types with a minimal loss of information compared to using individual surgical case types. This can be done by Ward's Hierarchical Clustering Method (16). We consider this method as most appropriate to use as a starting point for our solution approach in Section 5.

5 Solution approach

5.1 Modeling volume of dummy surgeries

Assume that our data concerns a period of one year without a trend that necessitates adjusting frequencies of surgical procedures in the upcoming period. We denote the length of a single MSS cycle by T and the number of repetitions per year by A. Then the volume of dummy surgeries that originates from surgery type c, as denoted by v_c, is calculated by

$$v_c := (\cup_{z \in Z^c} |I^z|) \bmod A \cdot T \tag{1}$$

5.2 Modeling resource demand variability

Putting two different surgical case types in one surgery type together leads to loss of information (regarding the resource consumption) compared to a situation where both procedure types are individually assigned to a surgery type. We base our solution approach on Ward's Hierarchical Clustering Method (16). This method uses the error sum of squares (ESS) as measure for the loss of information. Let ESS_c be the error sum of squares of surgery type c, which is computed by

$$ESS_c := \sum_{z \in Z^c} \sum_{i \in I^z} \sum_{r \in R} \left(X_{ir} - \frac{\sum_{z \in Z^c} \sum_{i \in I^z} X_{ir}}{\cup_{z \in Z^c} |I^z|} \right)^2 \tag{2}$$

Note that the different resource types r in Formula 2 are already scaled in X_{ir}. The overall ESS is determined by the sum of the ESS per cluster: $ESS = ESS_1 + ESS_2 + \ldots + ESS_C$.

5.3 Solution heuristic

To cluster surgical cases into surgery types we propose a modified version of Ward's Hierarchical Clustering Method. The basic outline, which is similar to most agglomerative hierarchical clustering methods (3), of this method applied to our problem is the following:

1. Start with N surgery types, each containing a single surgical case type z and an $N \times N$ symmetric matrix of costs $\mathbf{D} = d_{mn}$.

2. Search the distance matrix for the combination of surgery types with minimal costs. Let this combination consist of surgery types U and V.

3. Merge surgery types U and V. Rename the new surgery type as UV. Update the distance matrix by adding the new surgery type UV and removing U and V.

4. Record the intermediate set of surgery types and repeat Step 2 and 3 until one surgery type is left.

The elements of matrix $\mathbf{D}$ represent the additional costs of combining two surgery type compared to the current situation. This is calculated as follows:

$$d_{mn} = k_1(v_{mn} - (v_m + v_n)) + k_2(ESS_{mn} - (ESS_m + ESS_n)) \tag{3}$$

where k_1 and k_2 represent respectively the importance of the volume of dummy surgeries and the importance of the loss of information (increased variability).

The final step comprises of finding the best solution. Note that the optimal solution is not necessarily the initial solution, where the ESS is at a lowest level, or the final solution, where the volume of dummy surgeries is at the lowest level.

6 Case study

In this section we are concerned with the construction of surgery types for Beatrix Hospital, the Netherlands. Beatrix hospital is a regional hospital for primary hospital care. There are 5 inpatient and 3 outpatient operating rooms. The hospital has approximately 329 beds. Beatrix hospital currently implements the MSS approach as described by Van Oostrum *et al.* (12). Using an MSS, it aims to optimize operating room utilization and to improve the leveling of ward occupancy. As part of this implementation, the clustering techniques as described in Section 5 were used to propose surgery types for the MSS. The experiments were performed by the solution heuristic (Section 5) coded in MathLab version 7.0.

6.1 Data

To construct surgery types we obtained data of all elective surgical inpatients that were operated in 2006. From each patient we obtained, among other data, their surgical procedures, their length of stay (LOS) in the hospital, and their surgery duration (SurDur) ($r \in \{LOS, SurDur\}$). Surgical data was registered in the operating room by nurses and retrospectively approved by surgeons. LOS data was registered by nurses at wards for financial purposes.

To scale the resource variables, Beatrix hospitals assumes that one day admission equals one hour of operating room time in costs ($w_{LOS} = 1, w_{SurDur} = \frac{1}{60}$). Beatrix hospital considers implementation of an MSS with a length of either one or two weeks ($T = 1$ or 2). The operating room department runs on an annual basis during a period equivalent with 46 weeks ($A = 46$). Table 1 presents a summary of the Beatrix hospital data. In the first column all seven surgical departments are given. The second column presents the total number of patients (set I), while the third column presents the total number of different surgical cases ($r = 1, \ldots, R$). We solve the cluster problem in Beatrix hospital for each surgical department separately.

We vary the parameter values k_1 and k_2 indicating the importance of the volume of dummy surgeries relative to the loss of information. We take as values $k_1 = \{0, 0.5, 1, 5, 10, 20\}$ and keep k_2 constant at $k_2 = 1$.

6.2 Case study results

Table 2 presents the number of surgery types resulting after application of our solution heuristic. As can be expected the number of resulting surgery types equals the number of different case types in the data when $k_1 = 0$ is taken. However, when $k_1 > 0$ is taken the number of different surgery types sharply declines. Table 3 shows the increase in the loss of information (ESS) and the volume of dummy surgeries. This data can be visualized to determine the best trade-off between ESS increase and the volume of dummy surgeries, see for an example Figure 1. It is clear that obtaining the lowest volume of dummy surgeries lead to a high increase in ESS and contrarily that the lowest increase in ESS causes a high volume of dummy surgeries.

6.3 Discussion

In Beatrix hospital the proposed surgery types were used as input in discussions with surgeons to determine the actual surgery types. They checked for instance whether the surgical cases that were clustered in a single surgery type could be performed by a single surgeon. This enhances easy scheduling of surgeons. Surgery types were adjusted when required.

Another issue is whether the data of a previous year is representative for the upcoming year. We believe that in general the variability in length of stay and surgery duration in a upcoming period will be equivalent to a previous period. However, there may be trends in arrival patterns of patients. This may cause the need of adjusting frequencies of surgical cases, which in turn may cause that the solution heuristics would have produced a different set of surgery types. Beatrix hospital did expect trends in arrival patterns (for instance more hip and knee replacements). However, since such high volume surgical cases typically ended up in a surgery type without any other surgical case we have chosen to adjust frequency of surgery types after their construction.

7 Conclusion

In this paper we suggest a method for the constructing of surgery types to allow master surgical scheduling. The method is based on Ward's hierarchical cluster method that uses the error sum of squares as measure for the loss of information. We adjusted this model to account for the volume of dummy surgeries resulting from the clustering of surgery types, as this is important for the functioning of an MSS approach. The method was successfully applied to the case of Beatrix hospital.

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Surgical department	Number of patients	Number of different surgical case types	Mean surg. dur. (minutes)	Std. dev. surg. dur. (minutes)	LOS (days)	Std. dev. LOS (days)
General surgery	1428	153	72	56.2	2.7	4.7
Gynecology	783	47	57	43.8	2.3	2.4
ENT	1432	42	27	29.8	1.2	0.8
Eye surgery	1194	24	29	10.3	1.0	0.6
Orthopedic surgery	1751	89	47	37.5	2.2	3.0
Plastic surgery	369	20	39	25.3	1.6	3.2
Urology	434	53	71	68.6	3.4	2.7
Overall	7391	428	47	44.1	2.0	2.9

Table 1: Overview patient mix data Beatrix Hospital in 2006. Surg. dur. = surgery duration, Std. dev. = standard deviation, and LOS = Length of stay.

		k_1					
		0	0.5	1	5	10	20
T=1	General surgery	152-153	31	40	13	13	13
	Gynecology	47	14	14	5	2	2
	ENT	42	15	15	6	1	1
	Eye surgery	22-24	10	10	10	10	10
	Orthopedic surgery	86-89	17	17	5	6	6
	Plastic surgery	20	16	6	6	1	1
	Urology	53	22	13	13	13	5
T=2	General surgery	152-153	40	42	18	20	11
	Gynecology	47	16	13	7	5	5
	ENT	42	7	7	10	10	3
	Eye surgery	22-24	5	5	5	5	5
	Orthopedic surgery	86-89	29	19	7	7	7
	Plastic surgery	20	7	7	7	2	2
	Urology	53	22	23	15	15	15

Table 2: Number of surgery types in the best solution found for different values of k_1. Multiple solution are denoted as a range.

			k_1					
			0	0.5	1	5	10	20
T=1	General surgery	Increase ESS	0%	1%	1%	3%	3%	3%
		Volume dummy surgery	65%	13%	13%	7%	7%	7%
	Gynecology	Increase ESS	0%	1%	1%	8%	33%	33%
		Volume dummy surgery	82%	18%	18%	6%	0%	0%
	ENT	Increase ESS	0%	4%	4%	19%	60%	60%
		Volume dummy surgery	26%	7%	7%	4%	0%	0%
	Eye surgery	Increase ESS	0%	0%	0%	0%	0%	0%
		Volume dummy surgery	11%	4%	4%	4%	4%	4%
	Orthopedic surgery	Increase ESS	0%	1%	1%	4%	7%	22%
		Volume dummy surgery	37%	5%	5%	3%	3%	3%
	Plastic surgery	Increase ESS	0%	0%	1%	1%	11%	11%
		Volume dummy surgery	75%	25%	13%	13%	0%	0%
	Urology	Increase ESS	0%	2%	9%	9%	9%	81%
		Volume dummy surgery	79%	26%	15%	15%	15%	5%
T=2	General surgery	Increase ESS	0%	0%	1%	2%	4%	5%
		Volume dummy surgery	48%	11%	11%	5%	5%	5%
	Gynecology	Increase ESS	0%	1%	2%	11%	19%	19%
		Volume dummy surgery	50%	9%	6%	3%	3%	3%
	ENT	Increase ESS	0%	4%	4%	6%	6%	42%
		Volume dummy surgery	15%	2%	2%	2%	2%	0%
	Eye surgery	Increase ESS	0%	2%	2%	2%	2%	2%
		Volume dummy surgery	8%	2%	2%	2%	2%	2%
	Orthopedic surgery	Increase ESS	0%	0%	1%	3%	3%	3%
		Volume dummy surgery	21%	7%	4%	1%	1%	1%
	Plastic surgery	Increase ESS	0%	0%	1%	1%	5%	5%
		Volume dummy surgery	38%	13%	7%	7%	0%	0%
	Urology	Increase ESS	0%	1%	2%	10%	10%	10%
		Volume dummy surgery	68%	21%	21%	10%	10%	10%

Table 3: Trade off between the increase of ESS and the volume of dummy surgeries when k_1 is varied.

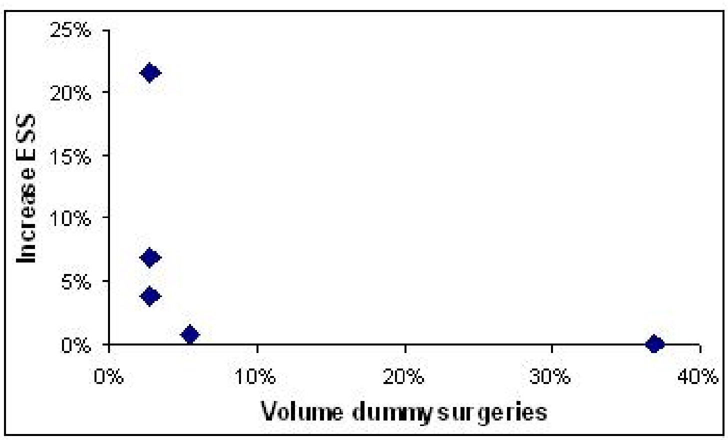

Figure 1: Visualization of the results of Orthopedic Surgery in case of an MSS cycle of one week. Volume of dummy surgeries is represented as a percentage of the total Orthopedic case volume.