E-HOSPITAL – A Digital Workbench for Hospital Operations and Services Planning using Information Technology and Algebraic Languages

Completed Research Paper

Introduction

One in every five Medicare beneficiaries in the United States is hospitalized one or multiple times each year (American Hospital Association, 2016). On the supply-side, almost 5,000 inpatient acute-care hospitals exist nationwide that treat these beneficiaries. Of the approximately $300 billion dollars spent on the Medicare program each year, almost $100 billion is spent on inpatient services (American Hospital Association, 2015).

Given limited budgets, hospitals seek to treat patients efficiently in order to stay profitable. Adapting inpatient services to new business models that aim to improve the planning of hospital-wide workflows for inpatients using operations management and advanced data analytics techniques are some of the recent developments that we observe in healthcare delivery (Gartner, 2015 and Gartner et al., 2015). In this paper, we propose a unified digital workbench to help multiple stakeholders in hospitals to improve the planning and allocation of scarce hospital resources to improve both transparency and efficiency of inpatient services. Additionally, we demonstrate feasibility of the proposed workbench by applying it for capacity planning decisions at a multi-hospital site using a preliminary prototype implementation.

Hierarchical Modelling of Organizational Decision Making

We draw on the classical hierarchical decision levels of Anthony (1965) to delineate different stakeholders' objectives for using our workbench at each decision making level. Anthony (1965) developed a model to break down business decisions into strategic, tactical and operational decision levels. Its essential aim was to assess the environment of a company and to adjust internal resources, accordingly (Clegg 1999). The model is depicted by the triangle shown in Figure 1.

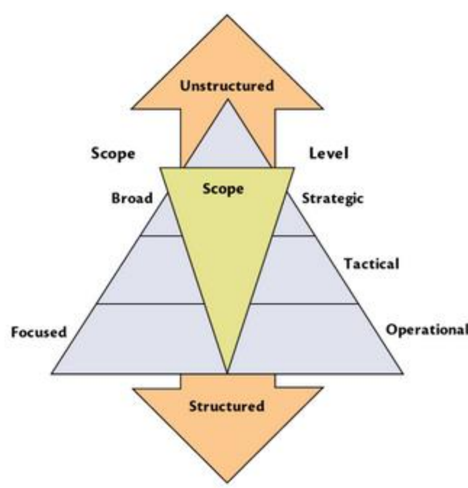

Figure 1. Hierarchical decision levels of Anthony (1965)

The figure reveals that the strategic decision level covers a broad scope and, the more a decision maker focuses on the operational level, decisions become focused. This is exactly how health care management decisions can be broken down. When strategic decisions are performed, decision makers focus on, for example, patient groups, rather than an individual patient which is the focus of, for example, scheduling decisions.

Despite its development more than 50 years ago, Anthony's (1965) framework is still well-accepted in IS research, as Arnott & Pervan (2012) demonstrate. By breaking down DSS publications into the classical hierarchies, their work reveals that the majority of business problems in DSS design science research published since 1990 focus on the operational level. In contrast, our E-HOSPITAL workbench combines all levels in one platform.

Stakeholders in the Decision Making

Table 1 provides an overview of different stakeholders who aim to understand the inefficiencies in hospitals, improve resource utilization or to maximize profit. We embed multiple mathematical models and their solutions approaches from the literature to support these objectives in an integrated decision making environment. End users such as healthcare analytics researchers and academics or hospital administrators and decision makers can use the proposed workbench to demonstrate/explore how mathematical models can improve resource planning and allocation decisions in hospitals. Furthermore, the workbench can be used in a Continuous Improvement Unit (CIU) of a health board that we will describe as a case study later in this paper.

	Stakeholder		
Decision making level	Board of Directors of Care Providers	Nursing/ Operating Room Manager	End Users such as Healthcare Analytics Researchers, Faculties, Members of Continuous Improvement Units
Strategic	Resource planning decisions	Staffing decisions	Demonstration of planning problems on all decision making levels, teaching operational excellence for members of staff in the health service
Tactical	Identification of bottlenecks in shift or other tactical planning decisions	Shift scheduling	
Operational	Identifying which elective patients may be responsible for increasing or decreasing profit margins for day-by-day planning	Appointment scheduling	

Table 1. Stakeholders of the digital workbench and decision making levels

The remainder of this paper is structured as follows. In the next section, we provide a survey of the relevant literature and position our decision support tool in the appropriate context. We then describe how we implemented the workbench and how we took into account features that are highly relevant for practice. We also illustrate the mathematical models by means of examples. In the following section, we demonstrate the application of the workbench in a case study based on demand and capacity planning for hip fracture patients using real-world data from two hospitals. We close the paper with conclusions and future work to include possible extensions into our workbench, specifically highlighting the opportunities that link the multiple levels.

Related Work on Decision Support Tools

An early review of evaluation studies of clinical decision support tools in medical informatics is Kaplan (2001) while a recent review that focuses on multi-morbid patients is provided by Fraccaro et al. (2015). More recently, Meulendijk et al. (2015) present a clinical decision support tool for physicians to optimize the patient's treatment plan and to avoid over-prescriptions.

Solving healthcare analytics and operations management problems in hospitals by means of a mathematical programming-based decision support tool has also been addressed in the literature. However, much more limited number of publications is available as compared to decision support tools which focus on the clinical or medical perspective. In what follows, we provide an overview of, in our opinion, the four most relevant decision support tools that integrate healthcare analytics and operations management for solving important and complex decision problems in healthcare delivery.

Joustra et al. (2011) introduce a strategic decision support tool for patient mix decisions by enabling the management to alter the number of patients in various patient groups. In a sensitivity analysis, the impact of changing input parameters on key performance indicators can be studied. The authors present a case study of the tool's application, but do not provide details on its software implementation.

A tactical decision support tool for cyclic master surgery scheduling (MSS) implemented in Visual C++.NET was developed by Beliën et al. (2009). The system visualizes the impact of the MSS on the demand for various resources throughout the rest of the hospital. This system displays the impact of switching two physicians on the expected resource consumption pattern and it supports decisions made on the tactical level.

Another software system that was successfully applied on an operational decision level in a hospital is called ORSOS. ORSOS is an enterprise-wide surgery scheduling and resource management system that automatically manages all surgical staff, equipment, and inventory using an engine that considers all of the clinical, financial, and operational criteria that must be addressed for each surgical event (Carter, 2000). Scheduling specific tasks, this tool supports decisions on the operational level.

Finally, Cayirli et al. (2012) develop an appointment scheduling model that is located on the operational decision level. It is implemented in an open-source online decision support tool and therefore not limited to a specific operating system.

It can be observed that the systems which were published in the literature so far only support one of the three hierarchical decision making levels, either focusing on the strategic, the tactical or the operational level. None of these applications integrate all three levels in one decision support tool that will eventually also allow opportunities to link solutions across the interfaces of these levels. As a conclusion of our search for related decision support tools, the main innovations of our E-HOSPITAL platform are two-fold: i) A unified, flexible and extensible workbench that combines different mathematical programs at the three classical hierarchical decision making levels is provided. ii) Formal, algebraic specifications of extensions of existing mathematical models are provided, implemented and can be solved to optimality using sample instances.

Implementation and Model Extensions

When implementing the workbench, we focused on widely acknowledged theoretical concepts from the decision sciences literature that breaks down planning problems into different decision levels. When developing our modelling extensions, we incorporated practitioner's feedback into the existing models.

Implementation of the Different Decision Levels

Using the design objective of Anthony (1965)'s triangle, seven approaches were selected from the literature that apply mathematical programming methods to provide decision making support for healthcare operations management problems. We also took into account the planning matrix of Hans et al. (2011) who provide a similar classification of problems on the strategic, tactical and operational decision making levels.

Strategic Decision Level

The top level of Anthony (1965)'s triangle, Strategic Planning, involves decision processes related to allocating resources, controlling organizational performance, establishing broad policies, and valuating capital investment or merger proposals (Power (2008)). Decision support needs to help managers envision the future and negotiate solutions with stakeholders while model-driven DSS can assist in some "what if?" analyses (Power (2008)).

These analyses is exactly what our workbench is aiming to provide: On the strategic level, Busse et al. (2013) and Blake & Carter (2002) were selected. Both papers decide on the case mix of patients in hospitals while capacity constraints are considered. The difference between the two models is that Blake & Carter (2002) have target levels of physicians for treating patients and target revenue of the hospital, among others. In contrast, Busse et al. (2013) follow an aggregate planning level to decide how many cases a hospital can support, given constrained resources. As a consequence, analyses can be run such as: Given operating room and bed capacity, what is the number of patients to be treated such that the hospital doesn't run into deficits. Another "what if" analysis is, given an increase or decrease in capacity, what is the impact on the number of patients to be treated for maximizing revenue.

Tactical decision level

Our environment's tactical decision level consists of the tactical admission problem as devised by Vissers et al. (2005). Moreover, we decided to include Master Surgical Scheduling (MSS) problems into that decision level. More specifically, we chose the approaches of Blake & Donald (2002) and van Oostrum et al. (2008). The difference between the two MSS papers is that van Oostrum et al. (2008) incorporate uncertainty into the planning while Blake & Donald's (2002) approach is entirely deterministic.

Operational Decision Level

On the operational decision level, Beaulieau et al.'s (2000) operational shift scheduling problem as well as Gartner & Kolisch's (2014) hospital-wide patient flow problem were implemented.

Model Extensions

Before implementing the different models, we extend them in order to increase their applicability: On the strategic level, we extended the work of Busse et al. (2013) on a temporal dimension. This allows users to insert expected values for different time periods for demand broken down by different diagnosis-related groups (DRGs). Another extension was the tactical planning problem of Vissers et al. (2005) in order to capture demand for physical therapists and therapy rooms in the admission planning of patients which we highlight in the next paragraph. On the operational planning level, we extended the model of Gartner & Kolisch (2014) in order to capture admission decisions of patients, among others.

Instead of formally detailing the extensions of all mathematical programs, we only show how we extended the model of Vissers et al. (2005). Its mathematical model is shown in the Technical Appendix. We incorporated physical therapy treatments into the model by introducing a (constant) therapy resource requirement of patients in each category. The resource requirement is typically measured in minutes. Now, if a patient of a certain category requires a physical therapy after admission, we denote this with a binary parameter. Each day after admission, the patient requires a treatment which is flagged by this Boolean indicator. On the supply side's extension of the model, we introduce physical therapists as well as therapy rooms. Both include capacities which can also be measured in minutes, for example 480 minutes of one therapist who has an 8 hours shift. Resource capacities are day-dependent in the case of human resources. We incorporate objective function weights for these resources into Vissers et al.'s (2005) original over- and under-utilization objective function. Additional constraints are, among others, that resource capacity constraints for therapy resources and therapy patterns have to be taken into account.

Examples when Using the Platform

Figure 1 and 2 provide examples of the tool. As can be seen in both figures, the tool separates strategic, tactical and operational decision levels using three tabs that are arranged vertically in the graphical user interface. Then, in each of the different planning levels, tabs are arranged horizontally which separate the different approaches from each other.

In Figure 1, one can observe that the case mix planning problem of Blake & Carter (2002) is selected and solved. The user interface shows pre-specified default values e.g. for the number of case mix groups desired for each physician or the hospital capacity (e.g. beds and operating room time). After solving the problem instance (using the corresponding button), the user can store the output in a text file which provides information about the generated solution. The figure reveals that the objective function value and the cases assigned to each physician are stored in the text file.

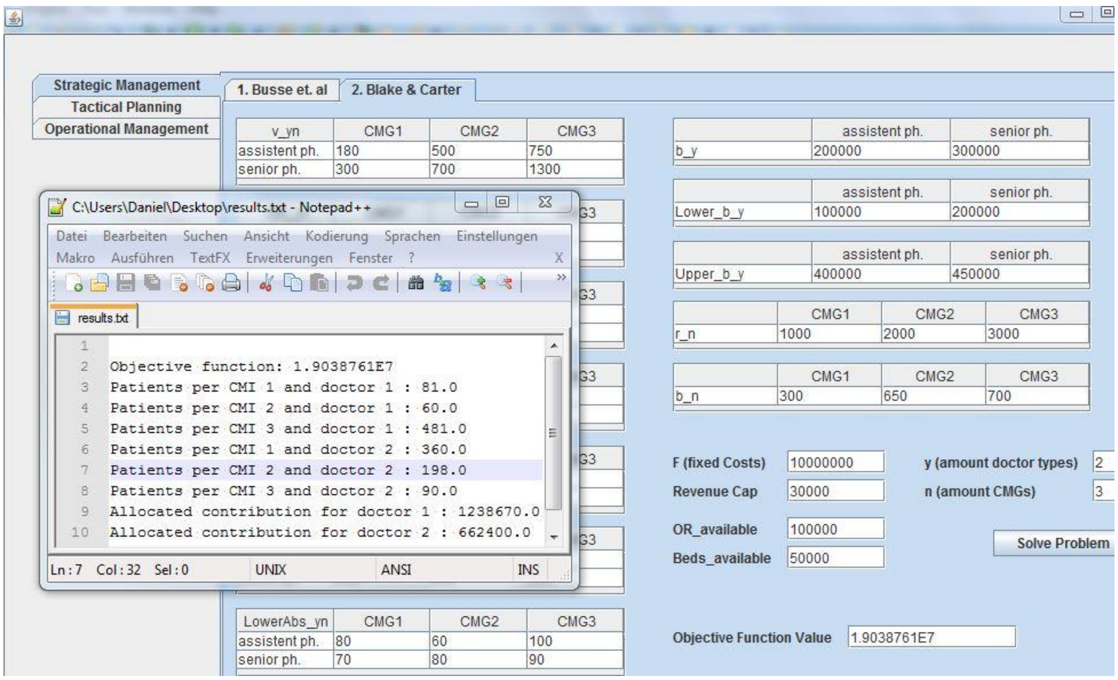

Figure 1. Blake & Carter's (2002) strategic approach

In Figure 2, the patient scheduling problem of Gartner & Kolisch (2014) is solved with some flexibility extensions for two patients. Flexibility extensions are, among others, that clinical activities such as surgeries can now be carried out in different modes: Each mode reflects a combination of skills and human resources that are assigned to an activity as determined by the scheduling decision variables. Besides the objective function value and schedule of each patient, the output reveals computational insights such as number of decision variables, constraints and solution time. The output also reveals in which mode each patient's activity is scheduled. For example, "activity 1 is scheduled in mode 2 on day 1" means that the admission activity of the first patient is scheduled on a different ward as compared to the ward which would have been assigned if mode 1 had been chosen. The output "activity 3 is scheduled in mode 1" means that the surgical activity is assigned to the first available surgical team. In contrast, for patient 2, mode 4 is assigned to the surgical activity. One explanation for this phenomenon is that the surgical team which is represented by mode 1, 2 and 3 is not available at day 9.

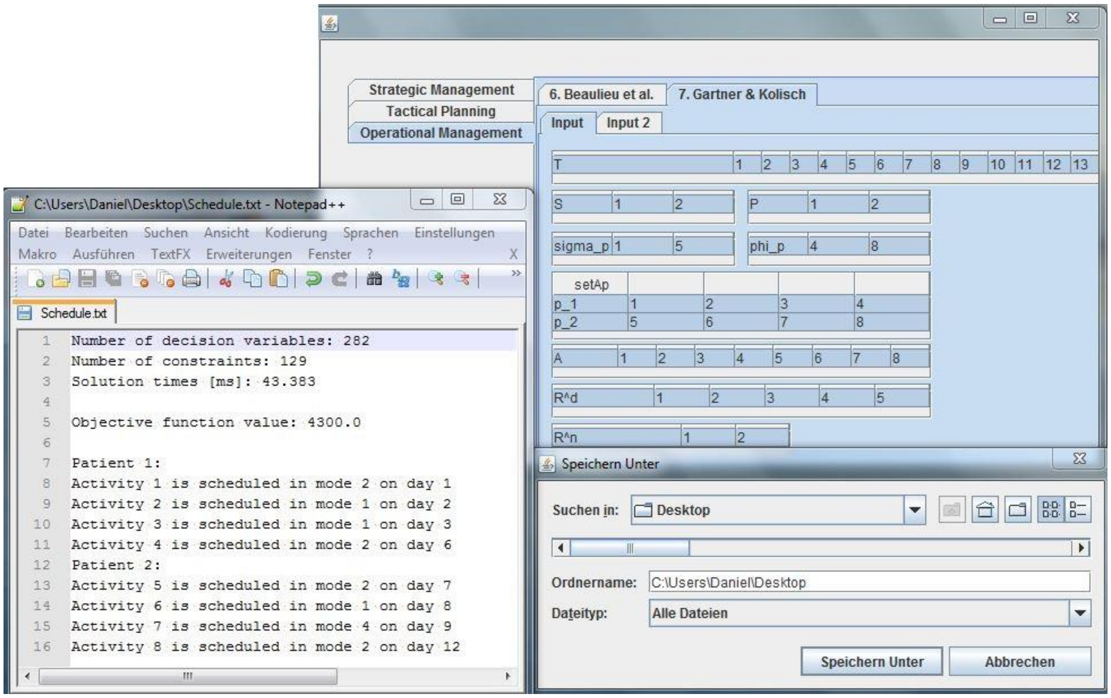

Figure 2. Gartner & Kolisch's (2014) operational approach

Especially, on the operation decision level this is useful because the decision support tool can provide quick consultation and approval (Mintzberg et al, 1976).

Installation Requirements and Platform-Independent Use

Before running the .jar file of the platform-independent environment, IBM ILOG CPLEX (2015) has to be installed. Also, at least version 6 of the Java Runtime Environment has to be installed. Figure 3 reveals that the platform can also be used on a MAC Operating System. The figure also demonstrates the large number of parameters that the user can enter into the workbench which is attributed to the complexity of Blake & Carter's (2002) model and the requirements from practice that the authors were faced with. For example, the user can enter a lower level of the number of patients each assistant and senior physician has to see for treating patients in the hospital. Further parameters are the availability of operating room and bed capacity in the hospital. As our case study will reveal, sometimes it is desired that the optimal operating room and bed capacity has to be determined by a model. Also, in some countries, revenue maximization is not the objective so that we have chosen to extend the strategic decision level by a third model which will be introduced next.

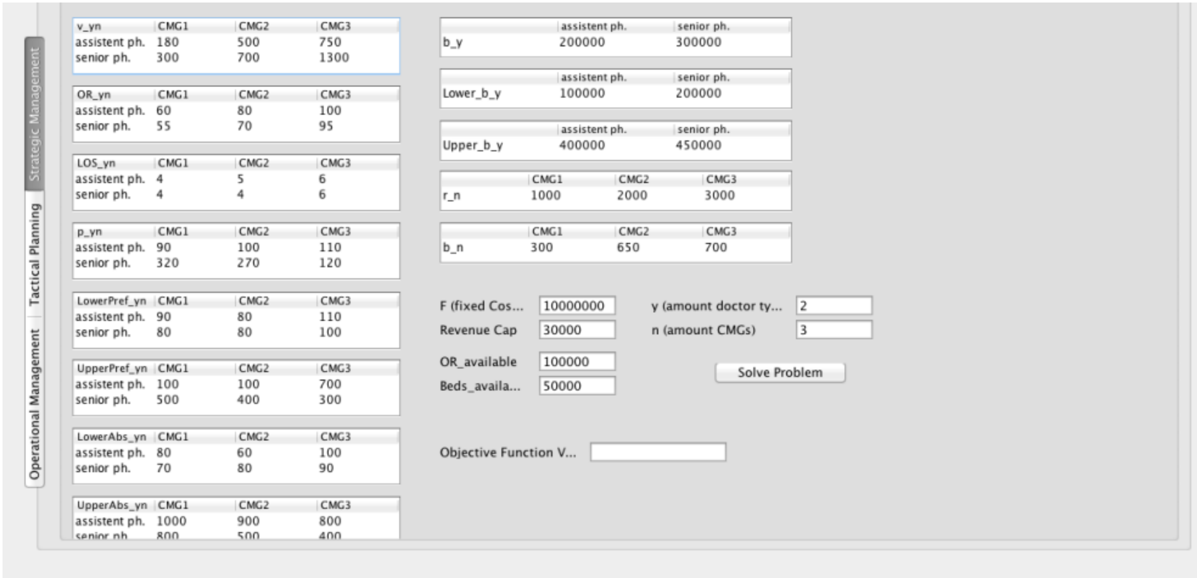

Figure 3. Overview of the Environment using MAC OS

Incorporating Capacity Planning into E-HOSPITAL – A Case Study

In what follows, we provide a capacity planning model and a case study for hip fracture patients by extending the E-HOSPITAL workbench presented so far. The objective of the case study is to show how the E-HOSPITAL workbench can be extended and used to account for a real-world decision making scenario. The task to be completed is to determine the optimal level of operating room and bed resource capacity required for treating hip fracture patients in a multi-hospital-site in the United Kingdom. This problem is obviously located on Anthony's (1965) strategic planning level because, rather than deciding on a narrow scope (see Figure 1) i.e. on individual patients on the operational level (e.g. scheduling decision), we decide on a broader scope (see Figure 1) which is less structured. Blake & Carter's (2002) as well as Busse et al.'s (2013) models seem at first glance highly suitable. However, the board of directors who will use the decision support tool in future, requires to determine the resource capacity level rather than the optimal number of patients given fixed capacities. Also, the board had specific usability requests e.g. to vary patient demand and lengths of stay.

The research questions which can be broken down into analytics and services planning are as follows:

- Analytics-focused research questions
  - How many patients require the service during a one year planning horizon?
  - What is the length of stay distribution of patient requiring hip fracture treatment in each of the hospital's catchment areas?
- Strategic planning questions
  - Fixing the catchment areas to the hospital-sites, what is the total amount of operating room time and bed capacity required?
  - Pooling hospitals, what is the resource requirement for each of the hospital?

Project Timeline

When carrying out the case study, we broke this project down into different phases as shown in Figure 4.

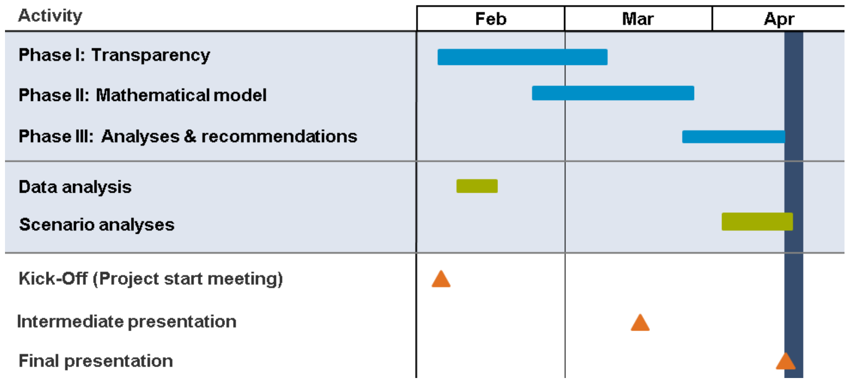

Figure 4. Hip Fracture demand and Capacity planning

In what follows, we will provide more details for each of the different project phases.

Transparency

In the first phase of the project which we called "Transparency phase", we evaluated the length of stay (LOS) distribution because, in healthcare, this can be seen as a major source of uncertainty. As the boxplots in Figure 5 reveal, the two hospitals that we studied (henceforth denoted as hospital 1 and 2) are faced with a large inter-quartile range of LOS. Moreover, the median LOS comes up to 28 days for hospital 1 and 23 days for hospital 2.

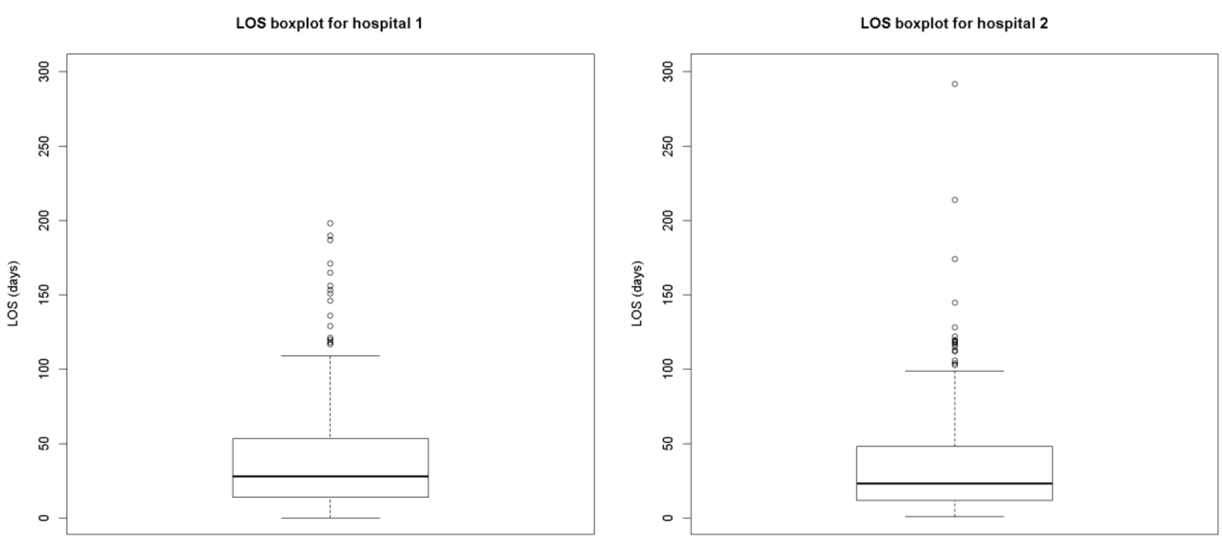

Figure 5. Boxplots of LOS distribution for hospital 1 and 2

A more detailed analysis of the LOS data using histograms, see Figure 6, confirmed the left-skewed shape of the LOS distribution which is similar to LOS distributions that can be observed in previous work (Gartner and Padman (2015) and Min and Yih (2010)).

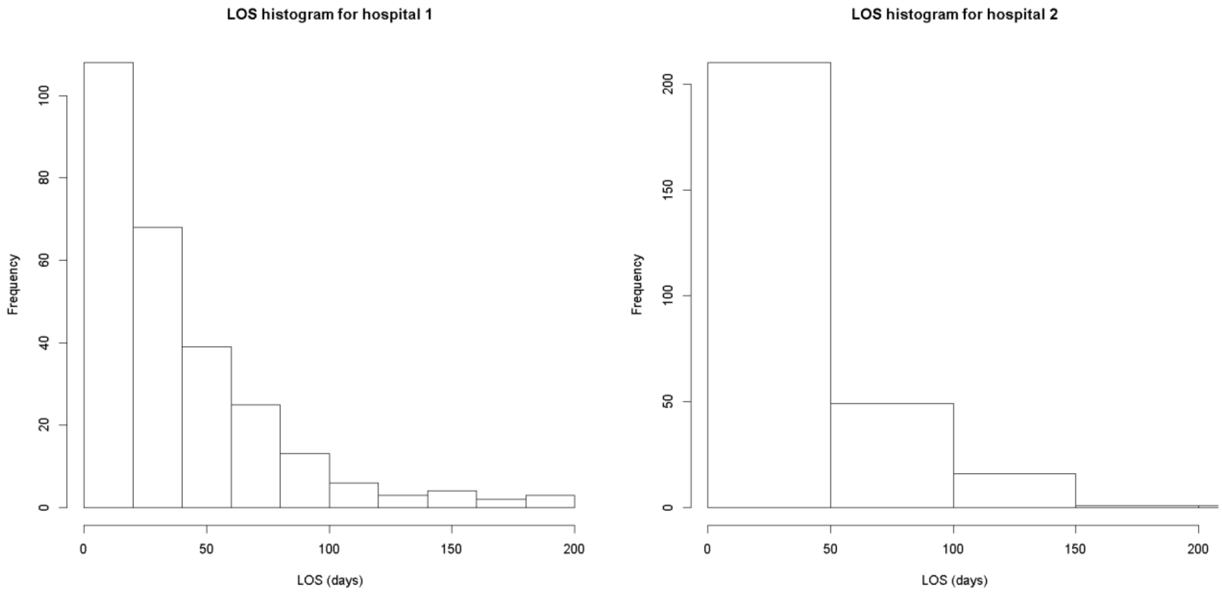

Figure 6. Boxplots of LOS distribution for hospital 1 and 2

Mathematical Modelling

In our mathematical modelling phase, we used the model provided in the Technical Appendix and incorporated it into the platform. The model was developed in collaboration with Orthopaedics physicians. In addition, the user interface was discussed in collaboration with the physicians and the Modelling Lead of the Aneurin Bevan Continuous Improvement Unit (ABCi). The result is shown in Figure 7.

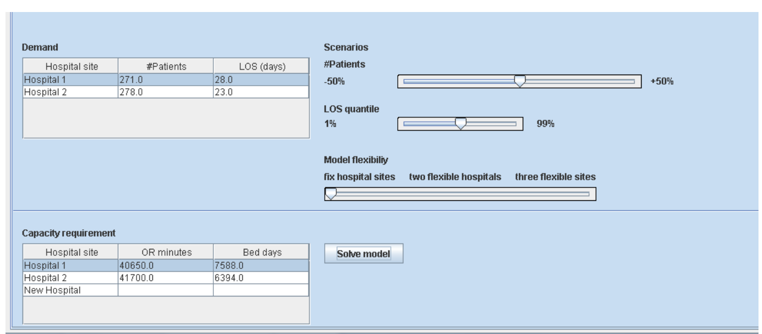

Figure 7. Integration of the model into the E-HOSPITAL platform

The upper part of the platform reveals that the patient demand reached 271 and 278 patients in the catchment area of hospital 1 and 2, respectively. Another observation is that the median LOS is 28 and 23 days for hospital 1 and 2, respectively. Manipulating the slider below the "#Patients" label and the slider below the "LOS quantile", we observe that, for example, we can run our analysis for +25% more patients and the 75% quantile for the LOS distribution. This reflects risk sensitivity for practitioners while ensuring that enough bed and operating room capacity is provided since demand is fluctuating.

Assumptions, Analyses & Recommendations

For our analyses, we assumed that the average duration of a hip fraction surgery is 2.5 hours. To determine the demand, we selected patients admitted to the Accident and Emergency Unit (A&E) in 2014 and patients who were discharged from the hospital in 2014. We set up two scenarios as follows: Scenario 1 consisted of a run where we used the median (50% quintile) for length of stay. Also, we focused on actual patient demand observed in 2014. Moreover, we ran the model with a fix assignment of patients to hospitals. This means that patients who arrive from hospital 1's catchment area are exclusively treated in that hospital. The same holds true for hospital 2.

In our second scenario, we include a third hospital (hospital 3) which will be built in 2017. In this scenario, the objective is to level bed capacity. Also, we bounded bed capacity to 28 beds in each hospital.

The results of the scenario analysis reveals that, using the fix model (scenario 1, see Figure 7), approximately 7,588 and 6,394 bed days are required for hospital 1 and 2, respectively. This corresponds to an average daily bed requirement of 21 and 18 beds, for hospital 1 and 2, respectively.

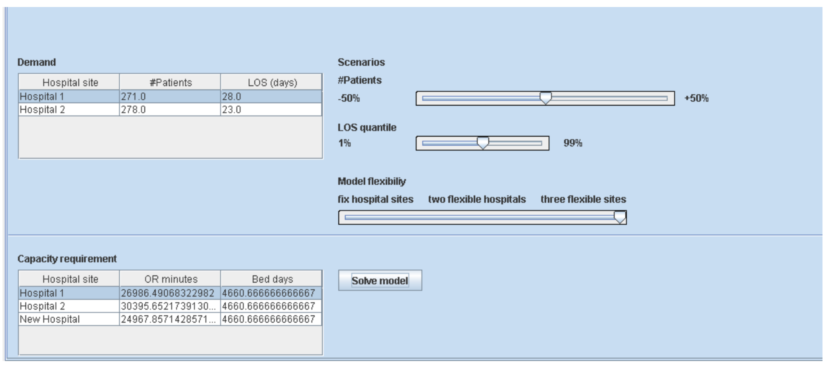

Figure 8. Results of the full-flexible model

Using the flexible model for three hospital sites reveals that 4,661 bed days are required for each of the hospital site. This corresponds to 13 beds. However, one can observe that the operating room capacity is different across the hospital sites which is attributed to the different patients' LOS. Less patients are admitted to hospital 1 but, due to their large LOS have the same bed but lower total OR capacity requirement.

Conclusion

In this paper, we have described the development of a unified digital workbench for hospital operations management which can be used not only by healthcare decision makers but also in education, including healthcare analytics and information systems courses. The tool combines the three classical hierarchical decision making levels in one integrated environment. At each level, several decision problems can be chosen. Extensions of mathematical models from the literature are presented and incorporated into the tool. In a case study using real-world data, we demonstrate how we used the workbench to inform capacity decisions in a multi-hospital site.

Future work will address the intersection between the different decision layers. Although, the intersection between, e.g., the strategic and the tactical layer have not yet been covered extensively due to the computational complexity, our aim is to provide at least quick and heuristic methods to evaluate the intersection between multiple decision layers.

Technical Appendix

Extensions for the Model of Vissers et al. (2005)

Planning Horizon, Patient Categories and Demand

Let $t = 1,...,T$ be the planning horizon with T as the latest period, e.g. 28 days. Let $O \subset \{1,..,T\}$ denote the subset of periods with days-off for therapists. Let M denote the number of patient categories and let ρ denote the resource requirement of a therapy session from therapists and therapy rooms which is measured in minutes. Let b_i be the number of days patients of category i stay in the hospital and let p_i denote the number of pre-operative days that category i patient requires. Let $\pi_{i,d}$ denote a binary parameter which is 1, if a patient from category i requires a physical therapy d days after admission and 0, otherwise.

Resources, Capacities and Utilization Deviation Weights

Let $r = 1,...,4$ denote the resource indices for ward beds, intensive care beds, nurses and operating rooms, respectively. In order to capture physical therapy resources, we extend Vissers et al.'s (2005) model and add resource indices $r = 5,6$ which are physical therapists and therapy rooms, respectively. Let $C_{r,t}$ denote the capacity of resource r on day t. Let w_5 and w_6 denote the weights for deviating from over- or under-utilization of the two physical therapy resources.

Additional Decision Variables

Let decision variables $V_{r,t,1}$ and $V_{r,t,1}$ denote the over- and underutilization deviations for the new resource indices $r = 1,...,6$ and let $H_{k,t}$ be a decision variable which gives information about the capacity required by all patients who seek admission and require resource r on day t.

Objective Function and Constraints

The reformulated objective function is shown in Equation (1) which minimizes deviations not only from the target throughputs for the resources introduced by Vissers et al. (2005) but also for therapy resources. We added Constraints (2) which calculate the over- and underutilization of therapists, the underutilization of therapy rooms (3), the resource capacities (4), the therapy pattern which is linked to the admission decisions (5) and Constraints (6) which ensure that on week- or holidays, patients are not scheduled for therapies. All other constraints of the model of Vissers et al. (2005) remain unchanged.

Minimize
$$\sum_{r=1}^{6}\left(w_r \cdot \sum_{t=1}^{T}\left(V_{r,t,1} + V_{r,t,2}\right)\right) \tag{1}$$

subject to
$$U_{5,t} - V_{5,t,2} \le \sum_{i=1}^{M}\sum_{d=1}^{b_i} \rho \cdot X_{i,t-p_i,-d+1} \le U_{5,t} - V_{5,t,1} \quad \forall t = 1,...,T \tag{2}$$

$$\sum_{i=1}^{M}\sum_{d=1}^{b_i} \rho \cdot X_{i,t-p_i,-d+1} \le U_{6,t} - V_{6,t,1} \quad \forall t = 1,...,T \tag{3}$$

$$U_{r,t} + V_{r,t,1} \le C_{r,t} \quad \forall r = 1,...,R, t = 1,...,T \tag{4}$$

$$\sum_{i=12}^{13} \sum_{d=1,...\delta_m:\pi_{i,d}=1}^{b_i} \rho \cdot X_{i,t-d+1} = H_{r,t} \quad \forall r = 1,...,R, t = 1,...,T \tag{5}$$

$$H_{k,t} = 0 \quad \forall r = 1,\dots,R, t \in O \tag{6}$$

Regional Capacity Planning of Hospitals

In this section, the capacity planning model of our case study will be described. We start with the definition of sets and indices, decision variables and their domains and finally present the model formulation.

Demand Regions, Patient Demand and Resource Requirement

Let $\mathcal{A}$ be a set of demand regions and let N_a be the number of patients observed in region $a \in \mathcal{A}$. Let $\mathcal{H}_a$ be the set of hospital sites that cover demand region $a \in \mathcal{A}$. l_a^p be the p percentile of length of stay coming from demand region $a \in \mathcal{A}$.

Decision Variables

Let decision variables C_h^{bed} denote the bed capacity required in hospital $h \in \mathcal{H}$. Furthermore, let decision variables C_h^{OR} denote the operating room capacity required in hospital $h \in \mathcal{H}$. Finally, we introduce $N_{a,h}$ which represents the number of patients from region $a \in \mathcal{A}$ treated in hospital $h \in \mathcal{H}$.

Objective Function and Constraints

Objective function (7) minimizes the bed and operating room capacity required for treating patients in each hospital. Constraints (8) ensure that the total patient demand in each area is the sum of patients treated across the hospitals. Constraints (9) links the length of stay for patients treated in each hospital to the bed capacity required in each hospital. Similarly, Constraints (10) link the operating room capacity requirement to the capacity level in each hospital. Inequalities (11)-(13) are the decision variables and their domains.

$$\text{Minimize} \quad \sum_{h \in \mathcal{H}} (C_h^{bed} + C_h^{OR}) \tag{7}$$

$$\text{subject to} \quad \sum_{h \in \mathcal{H}_a} N_{a,h} = N_a \qquad \forall a \in \mathcal{A} \tag{8}$$

$$\sum_{a \in \mathcal{A}_h} N_{a,h} \cdot l_a^p \leq C_h^{bed} \qquad \forall h \in \mathcal{H} \tag{9}$$

$$\sum_{a \in \mathcal{A}_h} N_{a,h} \cdot r^{OR} \leq C_h^{OR} \qquad \forall h \in \mathcal{H} \tag{10}$$

$$0 \leq C_h^{bed} \leq C_h^{bed} \qquad \forall h \in \mathcal{H} \tag{11}$$

$$0 \leq C_h^{bed} \leq C_h^{bed} \qquad \forall h \in \mathcal{H} \tag{12}$$

$$0 \leq N_{a,h} \leq N_a \qquad \forall a \in \mathcal{A}, h \in \mathcal{H} \tag{13}$$

In the case when we have a flexible assignment of patient demand to hospitals, a more appropriate objective is that bed capacity is levelled across the different hospitals. Therefore, we introduce objective function (14) which pursues this goal.

$$\text{Minimize} \quad \sum_{h \in \mathcal{H}} \sum_{h' \in \mathcal{H}: h \neq h'} \max\{0, C_h^{bed} - C_{h'}^{OR}\} \tag{7}$$

As easily can be seen, the objective is non-linear and we linearized it by introducing deviation variables and linking them with additional constraints.

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