A Generic Simulation-based DSS for Evaluating Flexible Ward Clusters in Hospital Occupancy Management

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Abstract

Hospitals facing competitive pressure, a fortiori unprofitable ones, should improve their efficiency. We propose low-investment opportunities uprating patient treatment by tactically implementing hospital-wide occupancy clusters raising bed resource allocation flexibility. We develop a generic simulation-based DSS to evaluate cluster configurations for a 1000+ bed university hospital. Besides current state of bed resources and patient flow, prospective scenarios with less beds—raising their utilization rate—and with 50\% more elective patients are evaluated.

Our data-driven DSS generates entire simulation models automatically from standard hospital data. Practical constraints like gender room separation and isolated infections treatment prevent underestimating bed requirements. Results show that clustering softens patient arrival peaks and induces dramatic reduction of bed bottleneck for all cluster configurations; yet more than 96\% when including an internal medicine cluster. Doubling this cluster’s size and introducing an interdisciplinary eleven wards surgery cluster induce the best-performing cluster configuration for bottleneck less-resource and more-patient scenarios.

1. Introduction

Health is the most valuable asset for humans. Keeping people healthy, however can become a difficult and expensive task, especially when focussing on hospital costs. These costs have been rising in Germany since 1990. According to rating reports of 2013, at least one third of all hospitals make a loss [1,4]. In order to break this trend, the German government decided to change the way hospitals earn their money. Since 2003 the diagnostics related groups payment system (DRG) is established. Since then, each German hospital earns an amount of money for each patient case which is computed by the treatment costs of benchmark hospitals. If the costs of treating patients are higher than in the benchmark hospitals, the hospital has to improve their efficiency or may become insolvent after some time [19].

One way to improve efficiency is managing the occupancy of the most expensive resource—inpatient beds [3], since most of medical and administrative resources is dependent on treatment (bed) capacity. Only with this, an effective patient flow management is possible [18]. Without this, hospitals have to face higher lengths of stay (LOS), idle expensive resources and bottlenecks within patient care [26].

In our previous simulation study on reducing waiting time of admission from the emergency department (ED) to an inner ward, we figured out that one very promising way of improving efficiency of occupancy management is to increase bed resource flexibility. For the University Hospital Halle (Saale) we achieved more flexibility by allowing patients to be admitted to a cluster containing all intensive care units (ICU) on the one hand and on the other hand allowing wards to borrow rooms from other wards nearby [11]. Encouraged by our findings, the hospital management decided to implement ward clusters to improve the flexibility of bed allocation and avoid bottlenecks in ICU and ED.

A cluster is defined as an amount of wards (hospital units or departments) which are able to nurse all kinds of patients of each single other ward of the cluster. Because of that, if the actual ward has no idle bed capacity, it is possible to admit a patient to another ward on the cluster. E.g. if a patient has an eye disease and the actual ward has no idle bed, each other ward of the corresponding head cluster is able to admit him. Without the cluster, the patient would have to wait or be rejected in the worst case.
Because of the complexity and the high amount of dependencies within hospital processes, changes are full of risk and uncertainty. That is why DSS (decision support systems) are needed to evaluate possible consequences of different occupancy policies [20].

With respect to existing literature on using simulation in the hospital context in general and supporting occupancy decisions in particular, this article pursues three main goals: First we will develop a simulation model which is able to simulate the whole patient flow of a hospital in order to evaluate three given cluster configurations. Second we will show, that practical constraints like gender separation in rooms and isolated nursing of patient with infectious illnesses have to be added to models for hospital occupancy decision support. Third we will show how our model can be integrated in a data driven decision support system for easy reuse within other hospitals.

In order to describe our current results, this paper is structured as follows: In the second section, we discuss the current state of the art of using discrete event simulation (DES) in hospitals generally, in occupancy management context in particular and derive the research gaps. Based on this, we show in the third section our concept of a simulation-based data driven decision support system. In the fourth section, we describe the three cluster scenarios which have to be evaluated. In fifth section, we show our results and discuss the consequences for the hospital. At the end we give a short summary and an outlook on further research opportunities.

2. Related Work

The use of discrete event simulation (DES) has a long tradition in the hospital context. Based on studies of scientific articles of the past 40 years Jacobson et al. conclude: “Discrete-event simulation offers perhaps the most powerful and intuitive tool for the analysis and improvement of complex healthcare systems” [12]. This statement is underlined with a big number of surveys [5,8,9,12,16,21,24] showing, that nearly every hospital related aspect has been investigated successfully. DES is mostly used for operational decision support like deployment, resource utilization or occupancy management [7,8,16].

Regarding to the large amount of literature, the low practical and theoretical benefits [7,8] question the sense of simulation studies in hospital context in general. “[..] there is no general sense of the literature moving forwards, because many papers tend to be reports of rather similar work on rather similar problems”[8]. Most of the studies are focusing isolated hospital departments, but this could be misleading with regard to the strongly complex and interdependent processes in hospitals [7,8,12].

To end this stagnancy in simulation science in hospitals, future studies should contain models that encompass the hospital and the relevant processes at whole, should lead to universal findings and practical benefit and could be reused or easily adapted to similar problems [7,8,9].

Particularly occupancy management is involved in nearly every hospital process [22]. Furthermore, Black and Pearson call inpatient beds “the most expensive resource” [3]. Based on this it is not surprising that there are a lot of articles focusing on the inpatient bed resource.

Because of the strong interdependencies between the wards of a hospital, only an approach which models more than one department, or the hospital as a whole could lead to valid results on bed capacity [23]. For this purpose we focus on related work that fulfill that condition.

Kim et al. used a simulation model to analyze the admission and discharge process of an intensive care unit (ICU). The authors successfully developed a simulation model that supports hospital’s administration to evaluate different policies for improving the ICU performance, show that the current capacity of 14 beds is sufficient at the current patient arrival rates and found some initial inferences how ICU performance could be improved generally by pointing to the managerial aspects and showing that the ICU’s capacity is not as important as the management of the other wards and its admission procedures [15].

In 2002 Harper und Shahani have shown that employing simple deterministic spreadsheet calculations to plan and manage bed capacities leads to underestimate true bed requirements. A realistic approach has to consider various types of patient flows at individual patient level and resulting bed needs over time. They underline that capturing the inherent variability of different length of stay distributions are important to develop planning tools for hospital capacities [10]. This confirms that misleading planning models are based on average length of stay, homogenous movement of patients through the system and ignoring the inherent heterogeneity of patients [25].

Costa et al. use simulation to estimate the number of required beds. The developed model is able to consider different admission criteria, priorities and expected lengths of stay based on the hospital’s own data. The authors underline this as the main strength of their approach [6].

Kolker developed a simulation model to figure out how many elective surgeries should be scheduled per day in order to reduce diversion in the ICUs. He shows that for his specific 450+ bed teaching hospital a
tradeoff between five surgeries per day with no length of stay less than 24 h would be best. In order to solve these kind of problems in general, Kolker describes three basic components that should be accounted for: the number of patients entering the system, the number of patients leaving the system and the capacity which limits the flow of patients through the system [17].

Khare et al. used a simulation model to show that altering the interval of admitted patient departure from the ED has more effect on length of stay than increasing the capacity of the ED [14].

Barado et al. analyzed patient data of 9 years and build a mathematical simulation model that is able to show the bed occupancy dynamics of the ICU at the Hospital of Navarra. The authors successfully developed a tool which is able to predict the bed occupancy rate and evaluate changes in patient admission factors like number of admissions of other hospital wards. They used their model to predict the number of beds needed in the ICU considering up to 50% more patient arrivals [2].

As mentioned in Section 1, we have developed a simulation model of a whole hospital to evaluate the effects on waiting time for patient admission from ED to inpatient wards of a university hospital with approx. 1000 beds in 2014. We analyzed hospital own data to model gender specific patient flows. In our results we found out that increasing flexibility by implementing occupancy clusters of ICU or the possibility to borrow rooms from other wards strongly reduces waiting time. Like [2,14] we could show that one key of increasing hospital performance is a more flexible occupancy management [11].

Encouraged by our findings in [11], the hospital management decided to implement occupancy clusters in the whole hospital and asks advice and assistance of our institute concerning simulation and evaluation.

Regarding to the related work on using simulation for decision support in occupancy management in particular and the critique on simulation based approaches in general, we address the following gaps: pursue a holistic view of the process through the hospital influencing occupancy management. For this we model the whole hospital and all necessary processes to evaluate different occupancy policies and we add practical room occupancy constraints in order to not underestimate bed capacity requirements. No other study takes these kind of constraints into account and we believe that our study will prevent producing misleading results as using average length of stay or homogenous patient flows [10,25].

Finally, we show a decision support system which is able to generate the model including structure and required distributions automatically by using hospital own data. Because of this data driven approach we reach a new level of generality which is beyond simple change of model parameters. We believe this kind of architecture is necessary to ensure easy reusability and adaptability of the simulation model to other hospitals.

3. Data Driven Decision Support System

3.1. Architecture

In order to build a reusable and extendable information system we choose a modular approach. Basically the system consists of three modules which are independently interchangeable. The basic structure is shown in Figure 1. In this proposal we use a data processing component, a simulation component and a central database.

The central database stores the raw data provided by the hospital and the generated data needed by the simulation component. We implemented a MySQL database to ensure that the other components are able to access the stored data. For a more detailed view of the data needed, see Section 3.2.

Once the data is provided in a predefined format the data processing component is able to generate empirical distributions and other control data used by the simulation component. A short presentation of the distributions is given in Section 3.3. With the use of our data processing unit the only requirement to create all distributions is to load the hospital data into our database and push a button.

We decided to use the Simio simulation software to implement the simulation component because of its strictly object oriented modelling approach. Every part of the created model is an object with its own logic. Furthermore, the basic simulation logic and the behavior of the simulation model is determined by the interaction of the objects. We use the standard interface to a MySQL database in order to pass empirical distributions and control data to the simulation model. For a detailed look at the simulation model see Section 3.4.
The architecture of our proposed system provides various options for adaptation and reuse. First, the proposed decision support system provides customization options at the architecture level. Changes can be carried out with reasonable effort due to the modular structure of the system. If parts of the system are changed it does not affect the other components as long as the new components provide an interface to the database. If we want to change the simulation model, we have to ensure that the new model uses the same distributions and control data. Otherwise we have to alter the data processing unit and the database too.

Furthermore this implementation is independent from the observed hospital, because we can use generic objects to automatically build the simulation model with the help of the provided data. So if we want to use this system to evaluate another hospital we only have to load the new data and start the system.

In general, our system offers a simple process to evaluate different scenarios in different hospitals. This process consists of six steps that are independent from the hospital investigated (see Figure 2). First, the user has to store the raw data in the database. After that, he uses the data processing component in order to generate distributions and control data. With help of this data the simulation component automatically generates a model and the user is able to configure the scenarios he wants to evaluate. After running the model, he is able to evaluate the generated outputs.

### 3.2. Data

In order to generate the distributions and the simulation model, input data provided by the hospital is needed. To ensure an easy-to-use system, we focused on simple data every hospital should record or should have access to. Building the model is based on infrastructure data and patient data of a hospital. To generate a model, we only need a list of wards and a list of available rooms according to the wards and the amount of beds in each room (see Table 1).

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<th>Infrastructural data</th>
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<td>Table 1. Required infrastructural data</td>
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Patient data we need is a record about every patient case passing the considered wards. If a patient visits four wards during its treatment at the hospital we need four records of this particular patient. Once more we focus on data which should already be recorded at the hospital like gender, LOS or whether this patient has an infectious illness (e.g. multi-resistant germs). The structure of patient data needed is shown in Table 2.

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<th>Patient data</th>
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<td>Table 2. Required patient data</td>
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For German hospitals, all these data can be found in the billing data set every hospital is obliged to create once a year due to the §21-KHentgG.

### 3.3. Data processing and distributions

The data described in the previous section is needed to generate empirical input data distributions. These distributions are mainly used to control the patient flow in the simulation model. In order to generate the distributions we use the data processing unit. Hence we calculate the number of arrivals for each day of week and arrival times. Additionally, we generate several other distributions describing for example the length of stay or the next ward a patient has to be transferred to. An overview of the distributions used in the simulation is given in Table 3.

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<td>Table 3. Distributions needed by simulation</td>
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Table 3. Distributions needed by simulation
Each presented distribution is conditioned on certain attributes. For example the distribution of the next ward depends on the gender of the patient and on the current ward. Because of that we have to calculate a distribution for the next ward for every ward and every gender. Furthermore we did not notice any seasonal fluctuations in arrivals or other data. Thus, we decided to generate these distributions to fit a representative week. A more detailed presentation of the distributions and their relationships is given in our previous study [11].

3.4. Simulation model

To achieve our main goal, to develop a hospital-wide simulation model for evaluating occupancy cluster configurations, we implemented a simulation model based on two inpatient flows. The flow of emergency patients and the flow of elective patients. The difference between these groups of patients is the starting point in the hospital. Emergency patients start their treatment unplanned in the ED, whereas elective patients can be scheduled and are directly admitted to a ward. At the ward, both patient groups compete for hospital beds. A schematic overview of the considered patient flows is given in Figure 3.

![Figure 3. Patient flows](image)

The presented patient flows were implemented in an object-oriented simulation model. Basically, this model consists of four custom objects we have developed using Simio. These objects represent the different departments of the hospital: hospital entrance, ED, ward and hospital exit, see Figure 4. The first object is the hospital entrance. Here the patients are generated and properties for each patient are set. Based on the computed distribution within the database each patient has the following set of properties: gender, infectious germ status and whether he is an elective or an emergency patient. Second, there is an object which describes the ED. The other components include the wards and the hospital exit. In the ED or at the wards, patients are treated. ¹ The hospital exit is used to collect several statistics. These objects altogether form the hospital which contains an additional allocation heuristic.

![Figure 4. Model structure](image)

A special feature of using an object oriented modelling approach is that the generated objects contain the processing logic. In our case the treatment process is encapsulated in the ward object. Basically, a patient is admitted to a ward, gets a treatment and is then discharged from the hospital or transferred to another ward. With these ward objects and the computed distributions we can easily create our model automatically. Furthermore the concept of object oriented programming offers additional concepts like inheritance or composition. For example, changing the behavior of some wards is easily be done by inheritance. In that case a new type of ward object will be created including some new logic without altering the original ward object. As stated before in Simio the simulation model itself is an object. Because of that we are able to build models of different hospitals and compose them to a model of a hospital infrastructure of a city for example. This can probably be done with reasonable effort.

To ensure a maximal possible number of patient allocations meeting all practical constraints on a ward after patient relocation, which is actually carried out by the hospital staff in practice, we implemented a separate patient room allocation heuristic. We consider two special constraints during the relocation, namely gender separation in rooms and isolation of infectious patients. The heuristic is triggered every time a patient should move to a new ward, to find a valid bed allocation on this ward. It consists of the following three steps:

¹ In detail, the ED object is an inherited ward object without any special characteristics so far. We created it as proof-of-concept.
1. All patients with an infectious disease are isolated distributed to the smallest rooms.

2. All remaining patients are distributed to the other rooms starting with the largest room: (case 2.a) if there are more men among the remaining patients, the largest available room is occupied by men. (case 2.b) If there are equal or more women, the next largest room will be occupied by women.

3. The heuristic ends if all patients were successfully distributed (valid assignment) or if no more rooms are available for the remaining patients (invalid assignment). In that case the heuristic fails.

If the heuristic fails, all patients that could not be assigned to a valid bed will be assigned to a virtual bed instead. We decided to use this concept because of the following reason: The provided data for the LOS on a ward consists of medically necessary stay time and a possible waiting time on relocation. Unfortunately, there is no possible way separate these times from the total LOS. If the patient in our model would have to wait for relocation, his LOS will be greater than in reality. In other words, the patient has to be relocated in the model after his LOS has been reached, because in reality this happened too. But where should the patient be located in reality when there is no valid bed available?

In practice, the hospital staff is quite creative in bridging the time until a valid bed is available. Thus we couldn’t model all real world possibilities, but we could measure them in our model. We do this by using the concept of virtual beds. This concept is also the key to evaluate the occupancy policies later on. If a policy leads to a higher amount of virtual beds more cheating has to be done because of occurring occupancy problems.

Summarizing the design of our object-oriented model approach, the used concepts enable the user to automatically create the simulation model and change or modify existing objects easily. Thus, the model offers many ways to adapt it to changing conditions. In addition the model can be used for different existing bed capacities. As mentioned in the introduction, our study in [11] shows benefits when considering flexible strategies for bed allocation to patients among nearby wards. The clustering concept should raise these benefits even more.

4. Occupancy Cluster Configurations

The University Hospital Halle (Saale) consists of 47 wards and one ED. The hospital has a total number of approx. 1,000 beds and approx. 33,000 patients are treated every year. To increase the flexibility of bed allocation the management decided to implement ward occupancy clusters. Each cluster will contain a number of wards. Within a cluster all kinds of patients could be nursed by each containing ward. At first every ward basically tries to use its own beds. If there is no more capacity for another patient, this patient will be admitted to another ward of the cluster which has available capacities.

The management created the cluster configurations (CC) shown in Table 4 based on organizational and medical reasons. These configurations should be evaluated in order to find the most efficient usage of bed capacities.

The proposed model enables the user to combine a clustering of wards with other scenarios. Thus, opportunities for capacity reduction, for increasing the number of patients and the change of admitting rules are offered. These possibilities can be freely combined.

5. Results

5.1. Validating the Model

In order to get correct evaluation results for the different cluster configurations we compare the behavior of the initial model with the hospital data. This model represents the current situation at the University Hospital Halle (Saale) without any clusters...
implemented. Because of comparing the different amount of needed virtual beds and the utilization rate of each ward later on, it suffices to make sure that all aspects of treatment capacity are correctly modeled. These aspects are: the total amount of elective and emergency patients treated within one year, the average LOS on each ward and the patient flows through the hospital.

According to the data of 2011, 24,598 patients were treated as elective patients and 9,087 patients entered the hospital as emergency cases. The following results based on 100 replications with a simulation time of one year. The average total number of patients generated in the simulation model were 24,707 elective and 9,064 non-elective Patients and matches the data.

As shown in Figure 5 the average LOS also shows only a slight difference to the sample data. The deviation varies between 2.1 % and -1.6 % and an average difference of 0.23 % could be achieved. Based on this the computed distributions for LOS are correctly.

Based on the results the validation of our model is successful. The computed distributions and the adoption of the represented week are working correctly. In summary, the model has a sufficient level of detail for evaluation occupancy policies.

5.2. The Influence of Practical Constraints

In this section, we address our second goal: showing that practical constraints which are important in daily routine of hospital must not be ignored in studies focusing on occupancy management. As mentioned in Section 3.4 we implemented two kinds of constraints, gender separation and isolated treatment. On the one hand, gender separation makes sure that in each room of a normal ward, only male or female patients stay. On the other hand, isolated treatment ensures that a patient with an infectious germ will stay alone in a room. We assume that these constraints strongly restrict the allocation of free beds, ignoring them will lead to a misleading models.

To compare the patient flow of our model with the given data we take a closer look on the total amount of treated patients within each ward. In general a patient is treated by more than one ward. That’s why we measured the total amount of treated patients in the hospital and on every ward. If our patient flows based on the computed distributions are correct, each ward will treat as many patients as in the data. Our model generated 45,013 treatments in total, which equals 45,172 total treatments given by the data. Figure 5 shows the difference in treated patients at each ward. It ranges from -11 % to 13 %. With respect to only three wards having a difference in treatments of more or less than 10 %, we assume that our model reflects the patient flows of the hospital sufficiently correctly.

We used our initial model as validated before and compared the amount of virtual beds needed with and without these constraints. As mentioned in Section 3.4 the usage of a virtual bed means that usually the patient could not be admitted and some kind of “cheating” has to be done. In the initial model, there was a usage of approximately 9,000 beds. By omitting these constraints less than the half (4,325) of virtual beds are needed. This difference confirms our assumption: Without these constraints the results of our study would be heavily biased.
5.3. Evaluation of Cluster Configurations

In order to evaluate the performance of the cluster configurations and to reach our third goal, we use two key performance indicators (KPI), the amount of needed virtual beds and the average utilization rate of the wards. As described in Section 3.4 represent each virtual bed needed an event of undersupply with available beds which have to be take care of. The utilization rate for each ward is computed by:

\[
\frac{\sum \text{occupied beds} + \sum \text{blocked beds}}{\text{number of beds}}
\]

*Occupied beds* are beds where a male or female patient is assigned. *Blocked beds* are beds within a room where an infectious patient is assigned. These beds can’t be used by other patients. We compute the utilization rate at 00:00 o’clock simulation time each day like the hospital does in reality. To thoroughly evaluate all cluster configurations, the actual scenario with current state of bed resources and patient flow is evaluated together with two prospective scenarios, one with less bed resources allowing 85% utilization rate; the other with 50% more elective patients:

- [S1] compare each cluster configuration with the initial model
- [S2] raise the utilization rate of each ward to approx. 85% by removing beds
- [S3] increase the amount of elective patient cases treated in the hospital by 50%

To enable the usage of the cluster within our model, we simply modified the allocation heuristic (see Section 3.4.). Now, before assigning patients to virtual beds if a ward has no bed available, the heuristic tries to find a valid allocation within the whole cluster. If even this fails, virtual beds of the actual ward will be allocated.

Figure 6 shows the total number of used virtual beds in [S1]. The initial model uses 9,135 virtual beds. In CC-1 746 beds were used. A further reduction occurred by using CC-2 (347 beds) and CC-3 (341 beds). The considerable reduction of virtual beds of almost 92% for CC-1 and more than 96% for CC-2 and CC-3 underlines the great potential of increasing flexibility in using resources. Regarding our second KPI, the utilization rate (shown in Figure 7) there has been no change. Values between 55% and 56% have been measured. Furthermore, high utilization rates could be eliminated by clustering the capacities. Based on these results, clusters that obviously are able to handle load peaks which means almost all patients could be treated with regularly available capacities.

Based on the results of [S1], we computed how many beds should be removed from each ward in order to obtain an average utilization rate of 85%. We computed the amount of approx. 354 beds that has to be removed from the hospital in total. To maximize flexibility within the wards, we removed beds to get as many small rooms as possible.

Figure 6 shows the amount of needed virtual beds and Figure 8 the average utilization rate for [S2]. The results show a distribution of work load between the wards and less unused capacities. However, this strategy aiming at an average utilization rate of 85% has big disadvantage because of less possibilities to respond to peaks. As result, the usage of virtual beds in all cluster configurations nearly reach the same level as the initial model. However, removing approx.
one third of all beds and the use of occupancy clusters still needs up to 31% less virtual beds than the initial model in the current state [S1].

To evaluate [S3], we increased the amount of treated elective patients by 50% to a total number of approx. 38,000. We didn’t change the amount of emergency patients, because the hospital can’t influence this figure. As shown in Figure 6 and 9, the average utilization rate increase as desired. The average utilization rate is now at 81% and the utilization of virtual beds ranges from 4,759 (CC-1) to 3,552 (CC-3).

Summarizing the evaluation results implementing occupancy clusters is better than the current state of the hospital in any case. Each cluster configuration is capable of handling peak loads in patient arrival. With regard to the number of needed virtual beds, CC-3 was best in all scenarios. However, the performance of a configuration is highly dependent on its composition because the improvement of efficiency is based on the more flexible usage of idle bed capacities within a cluster. If patient flows of wards belonging to a cluster are too similar, it is possible that no idle capacities are available when needed.

Furthermore our results indicate that the loss of flexibility by reducing capacity to increase the utilization rate leads to more problems in occupancy management than an increase of patient numbers.

6. Conclusion and Future Research

We successfully reached our main goal and developed a DES model of a whole hospital which is able to evaluate different occupancy cluster configurations. Improving bed allocation flexibility by implementing occupancy cluster had reduced the usage of virtual beds up to more than 96%. In all three scenarios (current state, reduce capacity and increase number of patients) the CC-3 had the best results.

From a medical point of view for the hospital, the introduction of an internal medical cluster in CC-2 and its extension in CC-3 seems to be crucial for an additional 50% reduction of virtual beds with regard to CC-1 already having 92% reduction. For prospective bottleneck less-resource and more-patient scenarios [S2] and [S3], CC-3 performed best, likely because of an additional big interdisciplinary surgery cluster. In contrast, omitting a big stomach cluster from CC-1 has no negative effects. This kind of results cannot be achieved without considering all patient data and their variations over the year, e.g. by simulation.

Model evaluations confirm our assumption that practical constraints like gender separated rooms and isolated patient treatment must not be ignored to avoid an underestimation of bed requirements.

To enable an easily reuse of our model, we finally embedded it in a data driven decision support system architecture. By doing this we could reach a new level of model generality. After entering hospital own data, we were able to automatically build the whole model including structure and distributions by pushing a button, instead of simply changing parameters.

In future research, we will try to find optimal cluster configurations by combining other operational research techniques like mathematical programming within our system.
7. References


