Agent-based Patient Admission Scheduling in Hospitals

Anke K. Hutzschenreuter[†‡]
a.k.hutzschenreuter@tue.nl

Peter A. N. Bosman[‡]
peter.bosman@cwi.nl

Ilona Blonk-Altena[§]
ilona.altena@cze.nl

Jan van Aarle[§]
jan.v.aarle@cze.nl

Han La Poutré[†‡]
han.la.poutre@cwi.nl

[†]Faculty of Technology Management
Eindhoven University of Technology, The Netherlands

[‡]Center for Mathematics and Computer Science
Amsterdam, The Netherlands

[§]Dept. of Planning and Management
Catharina Hospital Eindhoven, The Netherlands

ABSTRACT

Scheduling decisions in hospitals are often taken in a decentralized way. This means that different specialized hospital units decide autonomously on patient admissions or operating room schedules. In this paper we present an agent-based model for the selection of an optimal mix for patient admissions. Admitting the right mix of patients is important in order to optimize the resource usage and patient throughput. Our model is based on an extensive case analysis, involving data analysis and interviews, conducted in a case study at a large hospital in the Netherlands. We focus on the coordination of different surgical patient types with probabilistic treatment processes involving multiple hospital units. We also consider the unplanned arrival of other patients requiring (partly) the same hospital resources. Simulation experiments show the applicability of our agent-based decision support tool. The simulation tool allows for the assessment of resource network usage as a function of different policies for decision making. Furthermore, the tool incorporates a first optimization module for the resource allocation of post-operative care beds.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*; I.6.7 [**Simulation and Modeling**]: Simulation Support Systems

General Terms

Management, Performance, Experimentation, Design

Keywords

decision support tool; health care logistics; patient admission planning; agent-based modeling and simulation; agent-based planning

Cite as: Agent-based Patient Admission Scheduling in Hospitals, A. K. Hutzschenreuter et al., *Proc. of 7th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2008)- Industry and Applications Track*, Berger, Burg, Nishiyama (eds.), May, 12-16., 2008, Estoril, Portugal, pp. 45-52.

1. INTRODUCTION

Today, many hospitals face great demands to reduce costs and improve quality of service, e.g. by reducing waiting times. In several European countries this is due to the introduction of a free market health care system, for example in the Netherlands. In order to decrease costs, the occupancy rates of resources need to be increased and the length of stay of patients has to be decreased. However, increasing the resource utilization can lead to bottlenecks causing the blocking of patient flows and thus decreasing the quality of service. Therefore, efficient patient scheduling becomes increasingly important.

Admission scheduling is concerned with the selection of an optimal mix of patients to be admitted to the hospital, such that the available capacity and the demand for health care services are matched. A good patient mix facilitates an efficient usage of hospital resources through the combination of different profiles of resource usage. In health care, this problem is acknowledged to be complex, since hospital planners have to coordinate different patient treatment processes in which typically several hospital units are involved. Often, resources (like the intensive care unit (ICU)) are shared for multiple patient treatment processes. Moreover, the hospital planners have to cope with several sources of schedule disruptions: arriving emergency patients in urgent need for care, sudden changes in a patient's clinic state causing an unexpected transfer to an intensive care facility and/or the prolonged patient's stay. Complications or emergencies may lead to cancellations of operations.

Hospitals often show a distributed organizational structure [1]. They are divided into several autonomous hospital units, each associated with a medical specialty. Schedules of shared resources, like operating rooms, are managed locally by the units each applying their own (medical) priorities and preferences. Thus, patient scheduling in hospitals has strong decentralized features. A decision support system for this problem should therefore not only comprise advanced scheduling techniques that consider the dynamics of the problem, but should also reflect the distributed decision making and contain mechanisms to coordinate the schedules of the different parties involved. Therefore, an agent-based approach is ideal for decision support in this setting.

For a realistic study of the admission scheduling problem of different patient groups, we developed an agent-based simulation tool in a cooperation between academia and the Catharina Hospital Eindhoven (CHE), the Netherlands. The CHE is a large university-affiliated general hospital which offers international state-of-the-art medicine for, amongst others, cardiothoracic surgery (CTS) and intensive care in addition to the required basic medical care. In this paper we address the admission scheduling of CTS patients where each relevant hospital unit is represented by an autonomous agent. The following features are included: patient characteristics influencing the patients' priority and pathway in the hospital, uncertainty related to the duration of stay at the different hospital units as well as medical rules and preferences of the involved units. Resource availability is limited and uncertain due to the inflow of other surgical patients and the arrival of emergency patients. The latter may cause the blocking of patient throughput at the ICU. We base our work on an extensive data analysis and several interviews with experts from the CTS unit and the ICU of the CHE.

Simulation experiments demonstrate the tool's functionality. The patient throughput realized by the agent-based admission scheduling system is comparable to the performance of the human planners at the CHE. What-if scenarios allow for the evaluation of different scheduling and bed allocation policies. Additionally, an optimizer for determining an optimal bed allocation is incorporated based on a predefined objective function. To the best of our knowledge, this is the first agent-based model and simulation system for patient admission scheduling that includes multiple patient groups and resources and that is based on real hospital data and current scheduling practice. The agent-based simulation and evaluation tool is suitable for decision support in practice.

The remainder is organized as follows. First, we discuss related work in Section 2. Next, a description of the hospital domain and a model for patient flows is presented in Section 3. The agent-based simulation model with its decision structures and input and output elements is described in Section 4, followed by simulation experiments reported in Section 5. Finally, in Section 6 we provide our conclusions and an outlook on future work.

2. RELATED WORK

Earlier work in Operations Research mainly focused on single resources, such as operating rooms, intensive care beds or diagnostic facilities such as in [2] or [3]. We consider complex treatment processes requiring multiple hospital units. The work reported in [4] and [5] provide theoretical results for bed utilization levels for deterministic patient treatment processes. We offer a more operational approach which can deal with stochastic treatment durations and routing. Moreover, our approach is very flexible and can be easily adapted to other settings. The simulation model presented in [6] facilitates the evaluation of aggregated bed allocation policies. Our approach allows for an in-depth analysis of allocation strategies also on the level of different hospital units. Additionally, the effect of (small) changes in bed allocations can be evaluated using the agent-based simulation tool.

Also in the literature on agent-based scheduling, the hospital domain has been addressed. In [1] the issue of conflict handling in patient scheduling is studied. However, the dynamics of the problem, like stochastic treatment durations and stochastic routing, as well as different patient characteristics are not considered. Patient planning in [7] is based on medical wellness functions of patients. This solution, however, does not scale sufficiently and does not consider the stochastic features incorporated in our approach. Random treatment durations and routing between treatment steps are, however, very important to consider because they perturb the hospital units' schedules. Multiple appointments in an outpatient setting have been studied in [8]. Their approach assumes a predefined treatment path which does not hold in our problem setting. Also no stochastic appointment lengths were considered.

3. DOMAIN DESCRIPTION AND MODEL

3.1 Hospital domain

In general, a hospital can be divided into several, medically specialized, care units [1]. Hospital care units like nursing wards provide treatment and monitoring and are typically dedicated to a medical specialty such as orthopedics or cardiothoracic surgery. Hospital care units that are commonly shared by different specialties are the operating room (OR) unit, where medical specialties are assigned time slots for performing surgical procedures, and the intensive care unit (ICU), where patients with serious to life-threatening diseases are monitored. Often, the ICU is divided into several subunits characterized by different care levels. Care levels indicate the intensity of care and monitoring. We distinguish intensive care (IC), high care (HC) and medium care (MC), in decreasing order. Another important part of the ICU is the post anesthesia care unit (PACU) where patients recovering from anesthesia are monitored. Unless complications occur, patients stay at the PACU only for a few hours before returning to another hospital unit. Some hospitals also have designated ICU areas for medical specialties, e.g. the Coronary Care Unit (CCU) for heart disease.

We denote the set of care units relevant for our domain by U with U={CTS-OR, IC, IC-HC, MC, CCU, CTS-HC, CTS-PACU, CTS ward, o}[1]. o denotes the possible destinations of a patient's discharge from the hospital which are home or other care facilities, but also mortality.

For providing patient care at a hospital unit, resources are required. Relevant resources are ORs and hospital beds. Usually, ORs are available between 8 a.m. and 5 p.m. Hospital beds may also be opened only for a certain time period. This is typically the case at the PACU. We assume that resources are staffed and equipped with specialized facilities.

In order to accommodate patients at the appropriate care level, back-up capacity may be used. This means that an additional bed is opened at the respective care unit or that a patient is temporarily accommodated at another unit until a regular bed is available. At the CHE, the CCU serves as as back-up for the ICU. Usage of back-up capacity is undesired and will be accounted for in the output of our model.

3.2 Model of patient flows

[1]The prefix CTS indicates that a hospital unit is (partly) dedicated to CTS patients, e.g. OR time slots assigned to the CTS specialty. The HC is divided into IC-HC, which is shared by different specialties, and CTS-HC which occasionally allows other patients as well.

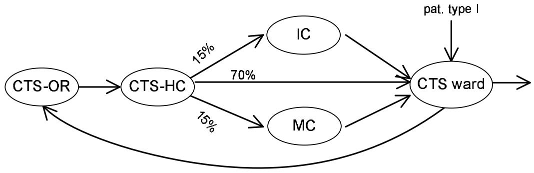

Figure 1: Representation of type I patient pathway[3]

We distinguish between scheduled patients (i.e. elective surgical patients from the waiting lists) and non-scheduled patients (i.e. emergency patients in urgent need for surgical and/or intensive care). Furthermore, we assume that patients can be grouped on the basis of their required treatment steps and respective expected duration. In a hospital context, the duration of a patient's stay at a hospital resource is referred to as Length of Stay (LoS). The above grouping of patients is commonly based on diagnosis related groups [9], expertise of medical specialists, or machine learning techniques as in [10].

The set of patient categories resulting from this grouping is denoted by C. We define a patient path (also referred to as pathway) of category $c \in C$ as the sequence of actually required treatment operations and the respective LoS. Specifically, we focus on complex (surgical) patient paths in which OR and different postoperative care departments are involved. All possible pathways of patient type $c \in C$ are modeled as a probabilistic graph [11], $G^c = (N^c, A^c, P^c)$, where the set of nodes, $N^c \subset U$, represent the involved hospital units and the set of arcs, A^c, represents the possible adjacent treatment operations. The length of stay of a patient of category $c \in C$ at hospital unit $u \in N^c$ is modeled as a random variable, LoS^c_u, that follows a probability distribution $P^{LoS^c_u}$. P^c is the set of conditional probability distributions defined on A^c with

$$P^c = \{Pr(v|u, c, t) | u \in N^c, (u, v) \in A^c, t \geq 0\} \text{ for } c \in C. \tag{1}$$

$Pr(v|u, c, t)$ represents the probability that care provided by unit v is required given that a patient of type c has been admitted to unit u for t time units.

3.3 Case study at CTS

The following is based on an extensive case analysis in the form of numerous expert interviews and data analysis. In the CHE case study for the CTS, four types of patient pathways (type I to IV) were identified. Type I and II patients are CTS patients, for whom the first postoperative care for type I and II patients is indicated as CTS-HC and CTS-PACU, respectively[2]. The type III pathway corresponds to the treatment process of emergency patients who arrive unexpectedly. The type IV patient path represents the inflow of other surgical patients in the system.The pathway of type I patients is depicted in Figure 1. Here, type I patients undergo surgery in the OR time slots allocated to the CTS specialty, denoted as CTS-OR. After surgery, they are admitted to the CTS-HC and are expected to return to the CTS ward on the following day. There is a 15% chance that complications require an admission to IC or MC[3] for type I

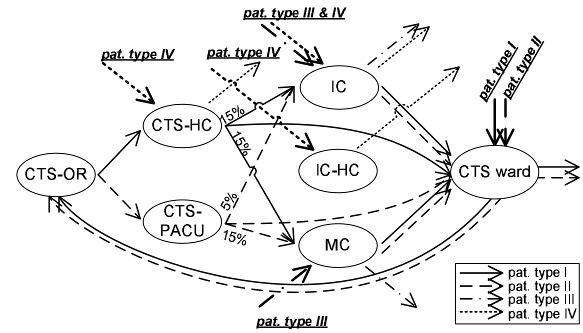

Figure 2: Interference of CTS, other surgical and emergency patient pathways[3]

patients[4]. Patients admitted to IC or MC are subsequently transferred to the CTS ward. If type I patients no longer require medical care and monitoring in the hospital, they are discharged and leave the system[5]. Figure 2 shows the four types of patient pathways and their interference. By dashed arcs, the possible pathways of type II patients are depicted. Type II patients follow a fast-track variant of the type I path. Postoperative care is performed at the CTS-PACU and type II patients are expected to return to the CTS-ward on the day of surgery. Severe complications occur rarely with corresponding probabilities of an IC or MC admission given as 5% and 15%, respectively[3]. Concerning type III and IV pathways, we focus on their possible interference with type I and II patients at IC, IC-HC, CTS-HC and MC. The preceding and successive treatment steps of type III and IV patients do not need to be considered because other dedicated resources are used. Type IV patients are primarily admitted to the IC-HC. If IC-HC beds are scarce, IC or CTS-HC beds may be used.

4. AGENT-BASED ADMISSION SCHEDULING SYSTEM

In the following, the agent system for scheduling patient admissions is described. For the analysis and design, the methodologies in [12] and [13] were taken into account. In the development phase, the model and system were frequently discussed with hospital planners at the CHE. The resulting system was approved by the CHE domain experts.

4.1 Overview

Figure 3 provides an overview of the architecture of the agent system. The system comprises two types of agent: OR scheduling agents and resource agents. The OR scheduling agent represents the CTS specialty and is responsible for managing the CTS-OR schedule. Resource agents act on be-

[2]The decision for a type I or II path is based on a preoperative assessment of the patient's clinical condition.

[3]The actual patient routing may deviate from the medical indication depending on the available beds at the respective hospital care units. Patients may only be transferred to a higher care level than indicated. The procedure is described in detail in Section 4.2.2.

[4]The ward round at the CTS-HC is scheduled at 10am during which patient transfer decisions are taken. This implies that the LoS at the CTS-HC can be considered as deterministic and t is irrelevant in (1). The same holds for type II patients at the closing of the CTS-PACU.

[5]Complications requiring re-admission or re-operation can be easily incorporated in our model. In the considered CTS case, however, they were irrelevant because they occur only exceptionally (in about 0.6% of the cases).

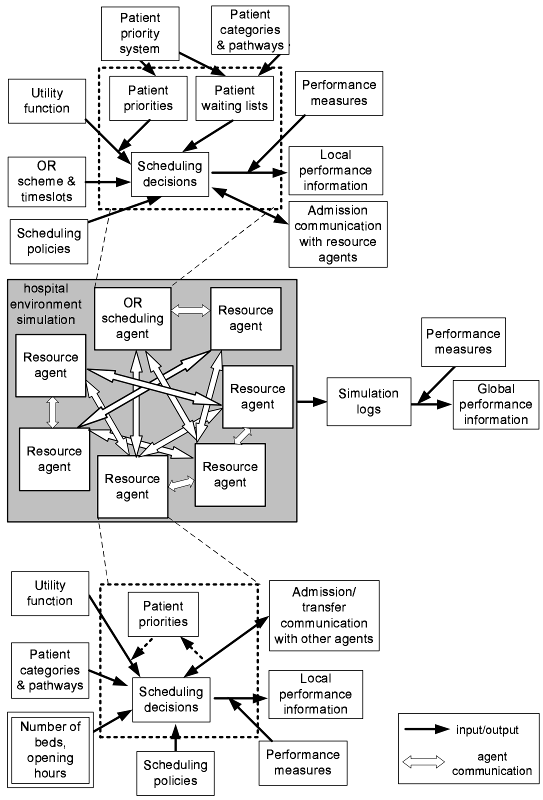

Figure 3: Architecture of the system

half of postoperative and critical care hospital units. Here, IC, IC-HC, MC, CTS-HC and the CTS-PACU unit and CTS ward are represented by resource agents. Resource agent coordinate patient admissions and discharges with other agents based on the patient pathway and their available resources. The in- and output elements and their relation to the internal decision structure of the OR scheduling and resource agents are shown in the upper and lower part of Figure 3, respectively. A detailed description of the agents' decision models is given in Section 4.2. The scheduling policies employed by the different agents are derived from the CHE case study and are outlined in Table 1. Table 1 also contains information on the number of resources allocated to the different units at the CHE. The CTS-OR is available from 8am till 5pm. Beds at the CTS-PACU and CTS-HC are opened for a limited time window. Hospital beds at the remaining units are opened day and night on 365 days per year (indicated as 24/7). Costs for different types of hospital beds relate to the daily costs for staff and materials and are expressed relative to the costs of a nursing ward bed.

The OR scheduling and several resource agents initiate part of their admission and transfer communication at fixed points in time. A time line is depicted in Figure 5.

In the present work, we consider the number of allocated beds and ORs as free decision variables (highlighted by double borders in Figure 3). Future work will also focus on the optimization of the agents' scheduling policies.

4.2 Decision model of agents

4.2.1 OR scheduling agent

Scheduling decisions of the OR scheduling agent depend on the availability of elective surgical patient groups on the waiting lists, and their medical priorities[6], e.g. [7]. The OR scheme specifies the number of patients of the different types to be scheduled to the allocated OR time slots, i.e. 2 half-day sessions for each of the 4 ORs. For the CTS, a half-day session corresponds to one surgery. The design of the patient pathway, described in Section 3.3, requires that early OR slots are assigned to type II patients. The agent's task is to schedule admitted patients to time slots according to the OR scheme. Also, the agent informs the CTS ward agent of the required number of patients of the different types for the following day's OR scheme and sends requests for postoperative transfers to the CTS-HC and CTS-PACU. The implemented policy is summarized in Table 1.

4.2.2 Resource agents

Admission and transfer decisions of resource agents depend on patient categories and pathways, bed availability, and the messages exchanged with other agents[6]. The resource agents' policies are described in Table 1.

In general, patients are admitted to a hospital unit only if beds are available. If more patients are proposed for admission than beds are available, a multitude of clinical variables determines which patients are admitted. We represent the medical choice by a stochastic process that randomly selects patients for available beds (excluding back-up capacity).

At the CHE, type I and II patients with IC indication are considered like emergency patients and are always admitted to the IC. If free IC beds are scarce, the IC agent may use back-up capacity which is accounted for in the system's performance. At the same time, one bed is kept free for type III patients. If the admission of type III patients is rejected by the IC agent, patients are admitted to another hospital which is left out of our model.

As analyzed at the CHE, the MC agent always accepts transfer requests from the CTS-PACU because CTS-PACU beds are closed at 22pm. If MC beds are scarce, patients are accommodated to back-up capacity.

If no bed is available at the indicated hospital unit, a resource agent approaches a resource agent of higher care level for transfer. We refer to this strategy as "upgrading" which together with the consecutive patient path is illustrated for type I patients by bold arrows in Figure 4. If a patient cannot be transferred to the MC, the CTS-HC agent approaches the IC-HC agent which normally is not intended. If the request is accepted, the concerned patient is "upgraded" to the higher care level. Otherwise, the next higher care agent is approached, i.e. the IC agent. If the transfer is not possible, the patient remains admitted to the CTS-HC until transfer to the CTS ward. The CTS-OR agent is informed of the limited admission possibilities.

The IC-HC agent applies upgrading for the admission of type IV patients for which the IC agent is approached first, followed by the CTS-HC agent. If upgrading is not possible, type IV patients are rejected. A rejected admission may affect the corresponding surgical specialty's OR schedule and may cause blocking at the dedicated nursing ward. Since only the resources shared with type I and II patients are considered in our model, the consequences of rejected admissions are not accounted for.

[6]For future use we included a policy module called utility function.

Table 1: Scheduling policies, resource availability and costs implemented in agent-based simulation system for patient admission scheduling

Agent	No. resources	Costs	Resource availability	Scheduling policy
CTS-OR Scheduling agent	4 ORs	-	Mo-Fr 8h00-17h00	request transfer of type II (I) from CTS ward to OR as specified in OR scheme at time S_{CTSII} (S_{CTSI}) (cf. Figure 5); if informed by CTS-HC agent that insufficient beds are available, type I surgeries are canceled accordingly; based on OR scheme for following day, inform CTS ward on required number of type I and II patients at time A_{I+II}; send transfer requests to CTS-PACU and CTS-HC agents after completed surgery of type II and I patients, respectively
CTS-PACU agent	4 beds	2	Mo-Fr 12h00-22h00	send transfer requests to hospital unit indicated for admitted patients at time $T_{CTS-PACU}$
CTS-HC agent	4 beds	2	Mo 10h00-Sa 10h00	send transfer requests to resource agents at time T_{CTS-HC} as described in Section 4.2.2; if transfer is rejected by all possible resource agents, patients remain at CTS-HC; inform CTS-OR agent of limited bed availability; accept admission of type IV patients if beds are available
IC agent	11 beds	4	24/7	admit all type I & II patients with IC indication; if IC beds are scarce, use back-up capacity; other patient admissions are accepted by random choice over patients contained in transfer request, one bed is retained for type III patients
IC-HC agent	4 beds	2	24/7	if insufficient IC-HC beds are available for requested type IV admissions, send admission request to resource agents as described in Section 4.2.2; if not successful, reject admission; admit other patients proposed for transfer by random choice to free beds
MC agent	4 beds	2	24/7	admit all patients from CTS-PACU; if MC beds are scarce, use back-up capacity; admit other patients proposed for transfer by random choice to free beds
CTS ward agent	35 beds	1	24/7	admit all postoperative patients; the number of preoperative admissions depends on the following day's OR scheme accounting for previously admitted patients whose surgeries have been canceled; if ward beds are scarce, use back-up capacity

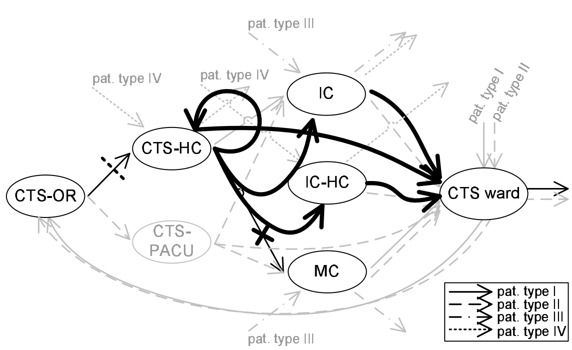

Figure 4: Current practice for type I patient "upgrading"

The agent model reflects the complex features of the hospital domain in a detailed and realistic way. The experimental system evaluation and validation is described in Section 5.

4.3 Technical details of implementation

The agent model is implemented in Java as an event-based simulation. Events are patient admissions and transfers. The system offers logging possibilities for actual scheduling decisions which is used to determine local and global performance according to predefined performance measures, e.g. number of treated patients or costs for regular beds.

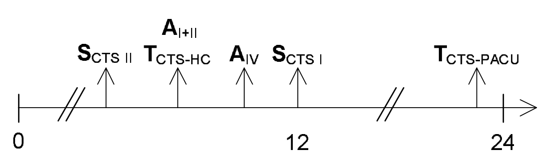

Figure 5: Time line for the fixed decision moments and communication: S - schedule surgery, T - transfer, A - admission and respective agent/patient type

Patient path information, i.e. the required treatment steps (including complications) and the respective LoS, are sampled at the start of a simulation run. The information disclosed to an agent is restricted to an event at the time a patient can be transferred or discharged. In the former case, the hospital unit to which the patient is to be transferred is indicated.

5. EXPERIMENTAL EVALUATION

5.1 Experimental setup

The settings of our simulation experiments are based on case analysis in the form of data analysis and expert interviews at the CTS department of the CHE. The relevant input parameters of the different patient pathways introduced

Table 2: Input parameters of patient pathways

Patient group	Unit	LoS (hours) mean±stdev	Routing prob.
Type I	CTS-HC	15 ± 0	-
	IC	48.48 ± 54	0.15
	MC	24.48 ± 38.52	0.15
	CTS ward	120 ± 22.08	0.7
Type II	CTS-PACU	6 ± 0	-
	IC	42 ± 57.12	0.05
	MC	10.32 ± 22.08	0.15
	CTS ward	120 ± 22.08	0.8
Type III	IC	37 ± 84.55	-
Type IV	IC-HC	100.27 ± 200.66	-

in Section 3.3 are given in Table 2. Models for sampling patients' LoS commonly used in the literature are Lognormal, Gamma and Weibull distributions [14]. We chose a Lognormal distribution because the use of it is simple and fast. Moreover, Gamma and Weibull distributions did not result in significantly different simulation results in the basic setting. We estimated Lognormal distribution parameters using the method of moments [15]. In accordance with expert opinion, "upgrading" does not affect the LoS of a patient.

In our simulations, type III patient arrivals follow a Poisson process with on average two patients per day. Bulk arrivals of type IV patients vary between 2 and 4 patients per day with a mode of 3. Patients of type I and II are elective surgical patients who arrive based on the admission schedule.

Patient inflow at the MC can be included in an abstract manner: the number of available beds is sampled at the start of a day using a discrete stationary probability distribution. This representation was chosen because type I and II patients are admitted to the MC for about one day (on average). This implies a minimal time dependency between subsequent days. Other patient inflow requires 3, 2, 1 or 0 beds with probability 0.2, 0.5, 0.2 and 0.1, respectively.

For the basic validation and evaluation of our system, we implemented the resource allocation policies currently employed at the CHE. An overview of the number of allocated resources and associated (relative) costs is given in Table 1.

The simulation system offers a number of outcome measures. Of particular interest to the hospital is the patient throughput, i.e. the number of patients discharged from the hospital after treatment. Also, the number of patients treated at the different hospital units, the frequency of external back-up capacity usage and the period of usage are of interest. In a hospital environment resource cost plays an important role. Here, we distinguish between the cost for "regular" beds and the costs for using back-up capacity. Regular costs are determined based on the bed capacity allocated to the hospital units, whereas back-up costs are calculated based on actual timely usage of back-up beds. The cost factors used for calculating costs are given in Table 1.

5.2 Experiments

5.2.1 Basic scenario and validation

In Table 3 the simulation outcomes for the basic setup, described in Section 5.1, are shown. The results were obtained from 50 simulation runs of 52 weeks each and a warming-up period[7] of 12 weeks. With the policies presented in Section 4.2, the agent-based admission scheduling system achieved a mean total patient throughput of about 3207 patients. Of this, 1768 patients of type I and II are treated with a standard deviation of approx. 40. Purely based on the CTS-OR capacity, a maximum throughput of 2080 type I and II patients could be realized. This upper bound is not realized in practice because the frequent blocking at the ICU affects the CTS-PACU and CTS-HC which in turn causes canceled CTS surgeries. At the CHE, about 1800 type I and II patients undergo surgery per year. Thus, the performance of the agent-based simulation system compares well to the human CHE planners. Regarding admission requests for type III and IV patients, the system achieves an acceptance rate of about 82.93% and 98.97%, respectively. These outcomes are comparable to recent aggregated measurements performed at the CHE.

Table 3: Simulation outcomes for basic scenario

Outcome measure	Mean±Stdev
Type I + II patient throughput	1768.08 ± 40.31
Type III patient throughput	539.16 ± 26.91
Type IV patient throughput	899.72 ± 10.28
Resource costs	
regular	38835 ± 0
back-up	355.65 ± 48.64

In our simulations, back-up capacity is used for about 50%, 25% and 25% of the cases for CTS ward, IC and MC. At the CTS ward, about 9.5% of the type I and II patients are admitted to another ward prior to surgery after which they follow the process described in Section 3.3. Postoperative patients are admitted to a back-up bed in about 8.5% of the cases with a mean LoS of about 16 hours. At the IC a back-up bed is required about once every three weeks for on average 16 hours. The frequency of back-up capacity usage at the MC back-up capacity is comparable to the IC, in total for about 26.7 bed days per year. Domain experts from the CHE have found the above results to be realistic.

5.2.2 Scenario analyzes

In many hospitals, an efficient allocation of resources to the different hospital units is a major managerial issue, especially because the relationship between beds, occupancy and acceptation rates for different patient groups is complex [6]. In order to address this problem, we analyzed several scenarios using the simulation system described above.

In the current situation at the CHE, about 10% of the preoperative CTS patients are admitted to other nursing wards because no bed is available at the CTS ward. Although the quality of care is not affected, admission to the CTS ward is preferable from a patient-friendliness point of view. Of course, the costs for patient-friendliness improvement through additional CTS ward beds should be moderate.

The results are given in Table 4. One additional ward bed, which increases total costs with about 1.7%, decreases the frequency of pre- and postoperative admissions to back-up beds by factor 3. Back-up capacity usage can be further decreased by additional ward beds with a minimum of about

[7] Warming-up was used to avoid starting with an empty hospital.

Table 4: Resource costs and frequency of back-up usage for varying number of CTS ward beds

	Number of CTS ward beds			
Outcome	35	36	37	38
Mean frequency back-up cap. usage				
preOR	9.51%	6.46%	4.07%	2.4%
postOR	8.54%	5.78%	3.57%	2.02%
Resource costs (mean±stdev)				
regular	38835	39200	39565	39930
back-up	355.65± 48.64	278.59± 33.33	226.11± 33.52	173.33± 27.28

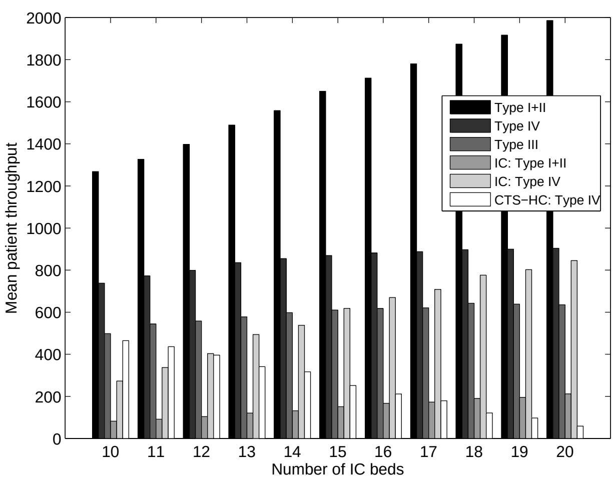

Figure 6: Mean patient throughput for 0 IC-HC beds and varying IC bed capacity

2% for 38 ward beds. Further increase of CTS ward capacity does not improve the resulting frequencies and was therefore not included in Table 4. Currently, the management of the CHE discusses the option of closing the IC-HC and transfer the bed capacity to the IC in order to be more flexible in patient admissions. Figure 6 shows the mean patient throughput per patient type for the above scenario and varying IC bed capacity. For increasing IC bed capacity, the mean throughput of type I and II patients increases linearly from 1268.4 to 1985.95 for 10 to 20 IC beds. The throughput of type III patients starts at about 500 and increases to about 620 for 17 IC beds (corresponding to an acceptance rate of about 96%) with a standard deviation of about 20. Thus, the variability in type III throughput is primarily determined by the variation of patient arrivals and LoS. The throughput remains almost constant for more than 17 IC beds. The same holds for type IV patients where the turning point is at 16 IC beds and 97% of the patients are accepted for admission. Interestingly, the treatment of type IV patients shifts from CTS-HC to the IC for increasing number of IC beds. This means that for increasing number of IC beds, the number of type IV patients treated at the CTS-HC decreases and increases at the IC.

Because of the shift in patient mix, 16 IC beds are required to guarantee the same overall patient throughput. 17 IC beds are needed to realize a comparable patient mix. Due to the interesting insights, we also compared other bed allocations for IC-HC and IC in terms of their cost-effectiveness. Here, cost-effectiveness is the ratio of mean total resource costs and mean total patient throughput. Figure 7 shows a contour plot of the mean resource costs per patient for IC-HC and IC beds varying from 0 to 10 and 5 to 20, respectively. The white cross indicates the current bed allocation at the CHE. The figure shows that resource costs per patient are convex with a minimum at about 6 IC and 6 to 8 IC-HC beds. Compared to the current situation at the CHE, this allocation increases the patient throughput of type I+II by 9%. Type III throughput decreases by factor 2, while type IV throughput remains almost the same. Costs for regular capacity are decreased by 16.9%, whereas back-up costs are increased by 70.9%. For 0 IC-HC beds, mean costs remain almost constant for increasing number of IC beds and decrease slightly for 14 to 16 IC beds. For this bed allocation, type I+II and IV throughput is decreased by about 12.4% and 6%, respectively, whereas type III throughput is increased by 8.9%. Regular costs are slightly increased by 3.8% while back-up costs decrease with 45.9%. These results can be explained by the interaction of different patient paths and its effect on the total patient throughput.

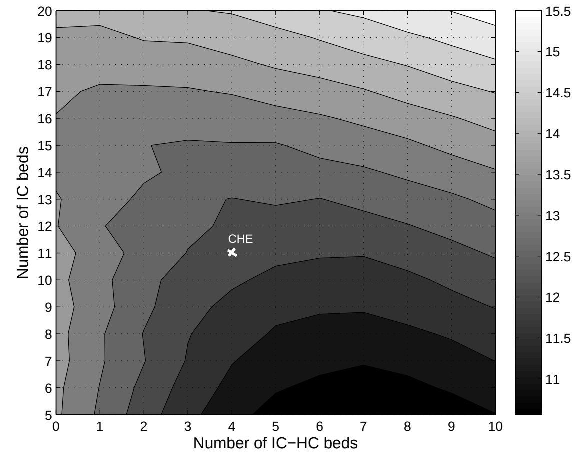

Figure 7: Contour plot of mean resource costs per patient for varying IC-HC and IC bed allocations

Thus, closing the IC-HC will affect the patient mix by increasing the number of treated type III patients and decreasing the throughput of type I+II and IV patients. The total patient throughput decreases slightly. Contrary to the discussion of the hospital management regarding closing of the IC-HC, increasing the IC-HC capacity seems advisable from a cost-effectiveness point of view.

5.2.3 *Optimization of bed allocation*

To automatically find an optimal bed allocation, we implemented a brute-force optimizer that uses the simulation system to evaluate different bed allocations. It can be used for various objective functions. The number of IC-HC and IC beds are varied from 0 to 10 and from 5 to 20 which results in 176 possible allocations. Each allocation was evaluated on the basis of 20 simulation runs of 52 simulated weeks and a warming-up period of 12 weeks. On an Intel Pentium 4 2.8GHz machine with 2GB RAM a simulation run takes about 13.1 seconds which resulted in a runtime of about 12.8 hours for the allocation optimizer. We illustrate the algorithm using the mean resource costs per patient as objective function. In the optimal bed allocation, the IC-HC capacity is increased to 7 beds and the IC capacity is reduced to 5 beds which results in resource costs per patient of 10.6 on average. The optimal allocation results in a mean annual total throughput of about 3100 patients.

6. CONCLUSIONS

In this paper we presented an agent-based simulation and evaluation tool for patient admission scheduling that realistically captures the complex features of the problem domain. To the best of our knowledge, this is the first agent-based simulation system for patient admission scheduling that includes multiple patient groups with stochastic arrival and treatment pathways. We showed that an agent-based model can be developed based on knowledge elicitation from the case that realistically reflects the problem domain. The implemented simulation system can be adjusted to comparable situations in other hospital settings. Furthermore, extensive simulation experiments demonstrate the applicability of the model and show how the agent-based simulation tool is useful for decision support. In a hospital setting where the planning is often performed in a decentralized way, a multi-agent decision support system is ideal because it allows for designing and evaluating improved (adaptive) policies, which can then be implemented easily in real life.

The multiple simulation outcomes for the basic setting show that the patient throughput achieved by the agent-based scheduling system is comparable to the planning performed by hospital staff of the CHE. Using the system new scheduling policies can be examined in a fast way: one year of hospital time can be simulated in a few seconds.

What-if scenarios show that the agent-based admission simulation tool can be helpful in analyzing the complex relationship between bed allocations, occupancy and patient mix. It allows a realistic analysis that otherwise would be impossible. Thus, the simulation system is of substantial value for decision support in practice.

We also presented a first approach to optimize resource management using the simulation model. Here, the free variables were the number of IC-HC and IC beds which appeared to have a significant influence on the overall patient throughput. The efficient computation and the size of the search space allowed using a brute-force optimization which guarantees a globally optimal solution. We illustrate the optimizer by using the mean resource costs per patient as objective function, but other performance measures can also be easily incorporated in the simulation tool. Optimally, the IC-HC capacity should be increased by 50% and the IC beds should be reduced by factor 2, compared to the current setting at the CHE. Due to its little variability in performance, the optimal allocation is a promising solution for practical implementation. The results show the multi-objective nature of the problem which will be addressed in future work. However, the benefit of a well-designed agent-based simulation for hospital scheduling becomes apparent.

It should be noted that in this study we consider situations for which waiting lists for elective surgery are sufficiently long, so elective patients are always available. This assumption holds for the Netherlands and several other European countries where the waiting list for cardiac surgery are long. In future work we will also address the online admission scheduling problem where waiting lists are filled dynamically and account for the patients' waiting time as measure of patient satisfaction. Moreover, we will develop an optimization algorithm for more than two resource categories using techniques from computational intelligence. Also, we will investigate possibilities for dynamic resource allocations.

The agent-based simulation and evaluation tool and the results were well received by domain experts and planners at the CHE. Because of the realistic modeling and the promising results, the system will be used at the CHE for further analysis and optimization of patient admission scheduling.

7. REFERENCES

[1] K. Decker and J. Li. Coordinated hospital patient scheduling. In *Proceedings of the Third International Conference on Multi-Agent Systems (ICMAS98)*, pages 104–111, 1998.

[2] P. Kolesar. A markovian model for hospital admission scheduling. *Management Science*, 16(6):384–396, 1970.

[3] P.R. Harper. A framework for operational modelling of hospital resources. *Health Care Management Science*, 5(3):165 – 173, 2002.

[4] R.J. Kusters and P.M.A. Groot. Modelling resource availability in general hospitals design and implementation of a decision support model. *European Journal of Operational Research*, 88(3):428–445, 1996.

[5] J.M.H. Vissers, I.J.B.F. Adan, and J.A. Bekkers. Patient mix optimization in tactical cardiothoracic surgery planning: a case study. *IMA Journal of Management Mathematics*, 16(3):281–304, 2005.

[6] P.R. Harper and A.K. Shahani. Modelling for the planning and management of bed capacities in hospitals. *Journal of the Operational Research Society*, 53:11–18, 2002.

[7] T.O. Paulussen, N.R. Jennings, K.S. Decker, and A. Heinzl. Distributed patient scheduling in hospitals. In *Proceedings of the Eigtheenth International Joint Conference on Artificial Intelligence (IJCAI-03)*, 2003.

[8] I.B. Vermeulen, S.M. Bohte, D.J.A. Somefun, and J.A. La Poutré. Improving Patient Schedules by Multi-agent Pareto Appointment Exchanging. In *Proceedings of 2006 IEEE International Conference on E-Commerce Technology (CEC/EEE 2006)*, pages 185–196, 2006.

[9] J. Vissers and R. Beech, editors. *Health Operations Management: Patient flow logistics in health care*. Health Management Series. Routledge, 2005.

[10] L. Maruster, T. Weijters, G. de Vries, A. van den Bosch, and W. Daelemans. Logistic-based patient grouping for multi-disciplinary treatment. *Artificial Intelligence in Medicine*, 26:87–107, 2002.

[11] B. Bollobàs. *Graph Theory: An Introductory Course*. Springer-Verlag, 1979.

[12] S.A. DeLoach, M.F. Wood, and C.H. Sparkman. Multiagent Systems Engineering. *The International Journal of Software Engineering and Knowledge Engineering*, 11(3):231–258, 2001.

[13] M. Nikraz, G. Caire, and P.A. Bahri. A methodology for the analysis and design of multi-agent systems using JADE. *International Journal of Computer Systems Science and Engineering*, 21(2), 2006.

[14] A. Marazzi, F. Paccaud, C. Ruffieux, and C. Beguin. Fitting the distributions of length of stay by parametric models. *Medical Care*, 36(6):915–927, 1998.

[15] J.L. Hodges and E.L. Lehmann. *Basic Concepts Of Probability And Statistics*. Society for Industrial and Applied Mathematics, 2nd edition, 2004.