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.

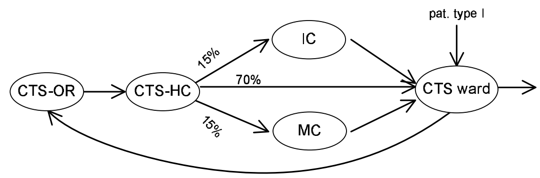

Figure 1: Representation of type I patient pathway[3]

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 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.

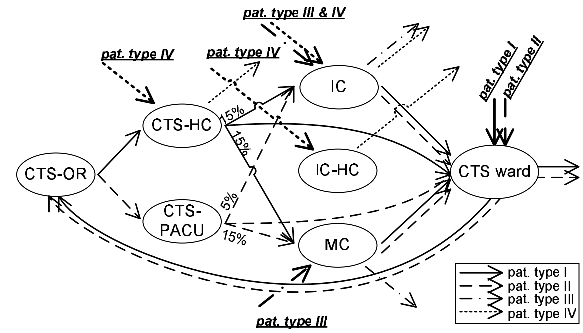

Figure 2: Interference of CTS, other surgical and emergency patient pathways[3]

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).