Patient Scheduling under Uncertainty

T. O. Paulussen, A. Zöller, A. Heinzl
Information Systems Department
University of Mannheim
Mannheim, Germany
{paulussen, heinzl}@uni-mannheim.de
wifo1@bwl.uni-mannheim.de

L. Braubach, A. Pokahr, W. Lamersdorf
Distributed Systems and Information Systems
University of Hamburg
Hamburg, Germany
{braubach, pokahr, lamersd}
@informatik.uni-hamburg.de

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1. INTRODUCTION

Patient scheduling in hospitals is faced with a high amount of complexity [4][5] due to the inherent dynamics of the processes and the distributed organisation structure of hospitals. For treatment, patients visit different units according to their illness [7]. However, the necessary medical treatments are often not completely determined at the beginning of the treatment process [5]. Further, the duration of the treatments are stochastic. Therefore, the main contribution of this paper is the introduction of MedPAge[1], a novel multi-agent based distributed approach to patient scheduling under variable pathways and stochastic process durations. First we describe the conceptual framework and then the current realisation of our coordination mechanism. This article closes with conclusions and an outlook.

2. CONCEPTUAL FRAMEWORK

In our multi-agent system for patient scheduling, patients and hospital resources are implemented as autonomous agents where the resource agents only see the patients as entities to be treated, and the patient agents only see the medical actions as tasks that need to be performed [5]. For the coordination of the patients a market mechanism is used [5].

To ensure feasible (i.e. conflict free) initial task appointments for the patients, all new treatments are scheduled on a *first-come first-served* (fcfs) basis [5]. Based upon this initial schedule, the patient agents try to improve their schedule through negotiation with other agents.

To be able to calculate bid and ask prices for time slots, we introduce health state dependent opportunity cost functions, where the disease of a patient is viewed as disutility (decrease in quality of life), which adds up as long as the disease is not cured [5]. These opportunity costs $C(t)$ equal the difference between the achievable health state through treatment z and the patient's health state development over time without treatment $H(t)$, which can either remain constant or decrease over time. In case of a decreasing health state we assume a linear reduction for practical reasons, i.e. $H(t) = s - bt$, where s denotes the initial health state and b the decrease rate [5]. From this we get

$$C(t) = \int_0^t z - H(t)\,\mathrm{d}t = at + \frac{b}{2}t^2; a = z - s.$$

To be able to consider stochastic treatment durations in the bargaining process, we calculate the *expected costs* $\tilde{C}$ for a starting time of a task by weighting the distribution of the starting time φ with the cost function $C(t)$ of the patient agent, i.e. $\tilde{C} = \int_{-\infty}^{\infty} \varphi C(t)\,\mathrm{d}t$.

Now the variance of the envisaged starting time can be viewed as risk (of delay), where a linear cost curve indicates risk neutrality (the benefit from the chance to start earlier compensates the disutility through the chance of a delayed start), and a convex cost curve indicates risk adversity (the possible gains from an early start are outweighed by the possible losses due to a delayed start) [8]. This should be illustrated by the following example equation, using a normal distribution for φ and our health state dependent cost function $C(t)$.

$$\tilde{C} = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \left(at + \frac{b}{2}t^2\right) \mathrm{d}t = a\mu + \frac{b}{2}(\mu^2 + \sigma^2)$$

We can see that the influence of the variance σ^2 depends only on b, which results as the determent of the agent's attitude to risk, i.e. *risk neutral* for $b = 0$, and *risk adverse* for $b > 0$ [8].

Based upon these cost functions, the prices the patient agents are willing to pay for a time slot result as the difference between the cost-value $\tilde{C}$ of the current allocation and the cost-value for the wanted appointment. Because the costs for a treatment increase over time, the patient agents must try to schedule their treatments as early as possible. If a demanded time slot is already occupied, the initial demander must try to buy the time slot from the current owner, which will only release their time slots, if the price offered equals the losses invoked through rescheduling [5].

To cope with variable pathways, the treatment process is divided into task-assignment intervals i (coupled with the ward rounds), in which the physicians determine the next set of treatments. While the assigned tasks can be scheduled directly, assumptions about possible future treatments have to be made. Based on empirical data we compute the probability $P_{v,i+1}(n_{v,i} + 1)$ of a treatment v to be assigned in the next interval $i + 1$ for the $n_{v,i} + 1$ time $(n_{v,i} \geq 0)$, where $n_{v,i}$ denotes the number of assignments of this

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task in previous intervals. To schedule these unassigned tasks, the duration d_v of these tasks v are weighted by their probability, i.e. $\hat{d}_v = P_{v,i+1}(n_{v,1}+1) \times d_v$. Through this, buffers according to the probability of the treatments are created in the resources. If a pre-arranged task gets assigned in the next interval, it will be scheduled at full length. Otherwise the task will be removed.

3. CURRENT REALISATION

The coordination mechanism presented in the previous section tries to overcome the traditional difficulties in hospital scheduling and needs to be tested against the existing mechanism and other approaches to validate its usefulness. To test the new mechanism, it is necessary to provide - besides the coordination core itself - an environment for simulating the approach in a hospital scenario. This allows for watching the coordination in action and for collecting statistical data, which can be used as objective comparison criteria. In the following an overview about the general architecture of our system "MedPAge" is given.

The multi-agent system is realized using the JADE agent framework and the Jadex extension for developing rational agents following the "Belief-Desire-Intention" (BDI) paradigm [6]. Foundation of the MedPAge simulation layer is a domain-independent agent-based and FIPA-compliant time synchronization component [2].

The core of the MedPAge system is composed of various interacting agents. Backbone is the simulation control agent which is responsible for starting all system agents. Task of the time service agent is the timely synchronization of all agents that participate in the simulation run while the event generator creates time points for important occurrences. Main actors of the system are the patient and resource agents, which negotiate appointment slots following the given coordination mechanism. The coordination mechanism itself and further needed functionality are encapsulated in separate agent modules, which are called capabilities [3].

When a simulation run is initiated, the information from the hospital model is used to create the hospital infrastructure consisting of initial patient and resource agents. During the run, an event generator agent uses different random distributions to approximate real arrival rates of patients and other occurrences like emergencies. The resource agents are notified by the time service when a treatment start time is reached, and try to call the patient. When the patient is unavailable due to another ongoing treatment, the treatment has to be delayed until the patient is available again. If possible, the resource will perform another treatment first. When a treatment is done, the actual treatment start and end times are stored in the database for later evaluation.

The coordination mechanisms have been designed using techniques such as AUML [1]. From the AUML diagrams the conversations an agent has to support were derived. In the MedPAge strategy the patient agent has a plan that pro-actively initiates the protocol for a single optimisation round, in order to improve the current schedule (see figure 1, left hand side). At the resource agent, reacting on the request of a patient agent, a plan is executed that manages the optimisation round by requesting other patients to free their time slots as needed (see centre of figure). Another plan is executed at a patient agent reacting to every subsequent request of a resource that a time slot has to be given away (right hand side). The resource determines that a new valid schedule has been created when no more reservations have to be moved. Then it checks if the new schedule is an improvement over the current schedule using the cost information supplied by the patients in the change-reservation requests. In this case inform messages are sent to all participating patient agents. All agents update their local beliefs and the resource agent also updates the MedPAge database with the new schedule. When the new schedule does not represent an improvement, failure messages are sent and the temporary schedule is discarded. In either case a new optimisation round may now be initiated by some other patient agent.

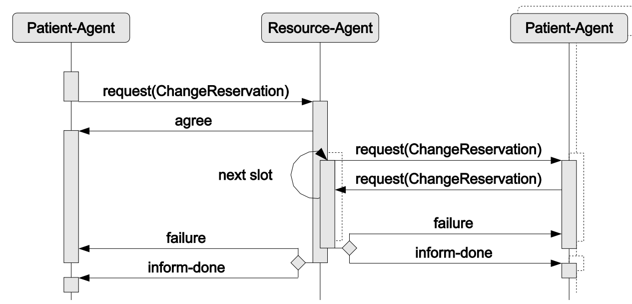

Figure 1: Coordination Protocol.

4. CONCLUSIONS AND OUTLOOK

In this paper, we described a multi-agent based approach to patient scheduling, in which patient agents negotiate with each other over scarce hospital resources, using health state dependent cost functions to compute bid and ask prices for time slots. Within this concept, stochastic processing times and variable pathways were considered. Further, we presented the architecture of our implemented multi-agent system, which is based on the BDI agent model and uses capabilities as a structuring concept. An agent-based simulation environment allows to compare different coordination mechanisms under equal conditions, using empirical data that was collected from hospitals. Future work will focus on further improvement and validation of our current coordination mechanisms using extensive trials and benchmarks. Final goal of our project is the deployment of the system into hospitals.

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