MULTI-AGENT BASED INFORMATION SYSTEMS FOR PATIENT COORDINATION IN HOSPITALS

Completed Research Paper

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Abstract

The health sector is a central domain in every economy. It is challenged by progressing costs and funding issues. Hospitals play a major role for the examination and treatment of patients. The sequence how patients are assigned to hospital units determines the quality of treatment, the resource utilization, as well as the patients' overall treatment time. Thus, efficient scheduling of patients in hospitals is crucial. Current approaches disregard the decentralised organization in hospitals and neglect the varying pathway of patients since they often focus on one single unit solely. We propose an agent-based coordination mechanism that overcomes these limitations. Patients and hospital resources are modeled as autonomous software agents which follow their own objectives. This reflects the decentralized structure in hospitals. Agents are coordinated by a distributed mechanism where software agents improve their situation through negotiations which moves towards an overall Pareto optimum. We show promising evaluations based on experiments.

Keywords: Patient Scheduling, Health Service, Multi-Agent Systems, Coordination Mechanism, Medical Pathways, Mechanism Design

Introduction

According to the OECD health data 2011, Western Countries spend above 10% of their GNP in the health care sector. In Europe, hospitals account for about 40% of all expenditures in the health care sector. Although hospitals offer vital and indispensable services for the people's health, they have become a significant cost factor in contemporary health care systems.

Despite the fact that the recovery and improvement of the patient's health is the primary objective, the underlying economic contingencies have become crucial for hospitals. The increasing cost and ongoing financing problems have led to structural changes in various national health care systems. Hospitals which are not cost effective may be merged into larger entities or eventually closed.

As a consequence, productivity increases and process orientation have become more important in hospitals. Key drivers are medical pathways, i.e. the examinations and treatments a patient requires during her/his stay in a hospital. From an operations research perspective, a pathway is a sequence of scheduled diagnosis and treatment activities. It determines a trade-off for utilizing capital-intensive capacity and the patient's length of stay (i.e. throughput times, including waiting times) in a hospital to assure health improvements.

Thus, patient scheduling in hospitals is concerned with the optimal assignment of patients to hospital resources. Hospitals are divided into several autonomous wards and ancillary units, which are frequented by patients for examinations and treatments during hospitalization (Mageshwari and Grace Mary Kanaga, 2012; Decker and Li, 1998). However, the pathways and the medical priorities (according to the health conditions of the patients) are likely to change since new evidence on the health state can be obtained during examinations or surgeries. Furthermore, complications and the arrival of emergency patients result in schedule disturbances (Vermeulen et al, 2009).

To sum up, patient scheduling in hospitals (1.) requires a distributed and flexible approach which fits the typically decentralized authority of decision making, (2.) captures the current state of treatments in a hospital, and (3.) allows to react to (internal and external) changes that affect a patient's health state in an effective and efficient manner.

Since operations research techniques often do not comply with the first requirement (Hutzschenreuter et al., 2008; Nealon and Moreno, 2003), a multi-agent based information systems will be developed for this problem. Multi-agent based information systems (MAIS) allow for the representation of coordination objects as single software agents which pursue own goals (Woolridge, 2002). This, in turn, complies with existing decentralized structures in hospitals (Decker and Li, 2000). The agents can interact with each other to reach their local goals. Moreover, they can react with the needed flexibility to state changes (as new information about the health status of a patient becomes available) and disturbances (e.g. emergencies and complications) through acknowledged properties like pro-activeness and responsiveness (Jennings, 2001).

This paper extents a deterministic multi-agent based coordination mechanism (Paulussen et al., 2003) through incorporating stochastic treatment times and emergencies. Patients are represented by autonomous software agents trying to improve their current schedule by negotiation with other agents. The negotiations are based on health state dependent opportunity cost functions on which the agents evaluate their current schedule and compute the gains and losses through plan modifications. This approach leads to a pareto-optimal situation from the perspective of the entire hospital.

We consider our extended coordination mechanism as a novel artefact. The multi-agent based IS serves to instantiate the properties and behavior of the coordination mechanism. The MAIS is modelled for multiple resources, emergencies, and stochastic service times.

The remainder of the paper is structured as following. First, we look at the foundations of the patient scheduling problem (PSP) and MAIS. Then, we present our novel coordination mechanism in a MAIS for the PSP. Though the focus will be on the conceptualization of the artefact, first evidence of its applicability is offered through initial evaluations. The paper ends with a conclusion as well as a brief outlook.

Theoretical and technological foundations

The Patient Scheduling Problem

Patient scheduling is characterized by the dynamic and distributed nature of the involved organizational units. Within a hospital, patients are either treated as inpatients or outpatients. Typically, patients are referred from a general practitioner, i.e. a medical doctor, to a hospital. In these cases, an appointment exists. In case of standard surgical interventions, the required preceding diagnostic procedures are often performed as ambulant treatments. Furthermore, walk-ins (without referral) and emergencies are additional cases that may occur. It's in the nature of diagnostics to gradually gain additional information about a specific symptom or disease. Thus, the medical pathway of a patient is subject to frequent changes. In this context, even an outpatient visit can require several, partially non-anticipated examinations and may even end-up in a hospitalization.

The schedule is basically a list of units that have to be visited by the patient where either a treatment or an examination takes place. Next to (mutual exclusive) treatments and examinations requiring the attendance of the patients, there are also patient-independent tasks such as evaluating diagnostic results or laboratory examinations. In the context of this paper, we focus only on patient-dependent tasks. The patient moves from one unit to the next one where he may need to wait until he is treated or examined. While inpatients (if already admitted) can return to their ward for waiting times, outpatients obviously cannot. In this context, patient-bounded tasks for outpatients cannot be easily postponed to the next day.

The initially scheduled list of units to be visited is not stable over time. Even without external factors, the pathway of a patient can change, e.g., due to new insights during an examination. External factors, such as emergencies, may lead to additional waiting times or can cause the rescheduling of a medical path. The distributed nature of a hospital's organization leads to a complex PSP that does not permit the application of traditional scheduling techniques (Mageshwari and Grace Mary Kanaga, 2012, Vermeulen et al, 2009, Kumar et al, 1993).

Earlier work on the PSP mainly focuses on single resources or units such as operating rooms, intensive care beds or diagnostic facilities (Harper and Shahani, 2002). Other contributions provide results for bed utilization levels for deterministic patient treatment processes (Kusters and Groot, 1996), (Vissers et al, 2005), resource conflict handling in patient scheduling with deterministic treatment durations (Decker and Li, 1998) or deterministic patient scheduling (Paulussen et al, 2003). (Vermeulen et al, 2006) study multiple appointments for outpatients, but assume predefined, i.e. static treatment paths. (Hutzschenreuter et al, 2008) offer a MAIS for patient admission scheduling which attempts to optimize the mix of patient types (but not the schedule itself) in order to improve the scheduling pattern for type specific pathways. (Vermeulen et al, 2009) focus on an urgency based scheduling algorithm which plans for another single resource (i.e., Computer Tomography) in a highly specific setting (i.e., a specific Dutch hospital) which is close to reality but limits generalizability. For an overview see also (Mageshwari and Grace Mary Kanaga, 2012) and (Nealon and Moreno, 2003).

As a consequence, the literature lacks a comprehensive approach, which

- entails a patient's complete treatment path (i.e. multiple units and resources),
- quickly responds to changes within or outside the entire treatment environment (e.g. changing health states of patients, arrival of emergency patients, outages of physical resources, etc.),
- still maintains a high level of decentralised coordination and mutual adjustment,
- is generic in a sense that it can be applied to other hospitals, not specific settings only.

Multi-Agent Based Information Systems

A multi-agent system is a loosely coupled system of problem solvers without global system control (Davis and Smith, 1983), where a single agent has generally only partial observability and control over the entire environment (Jennings et al, 1998). The software agents are used to solve problems that are difficult or impossible to solve for a single software agent or a monolithic system. In this context, the several agents represent the decentralised nature of the problem as well as multiple perspectives and competing interests (Jennings, 2001).

Software agents in a MAIS have several important characteristics (Wooldridge, 2002), (Panait and Luke, 2005):

- Autonomy: the software agents are autonomous;
- Locality: No agent has a full global view of the system or the system is too complex for an agent to make practical use of such knowledge;
- Decentralization: there is no designated controlling instance which coordinates the behaviour of the entire system.

Thus, MAIS can be referred to as "self-organized systems" which try to find the best solution for their problems without the intervention of a central controlling agent. These characteristics offer a high similarity to characteristics of hospitals where the organizational units coordinate themselves on the basis of mutual adjustment. These units are autonomous, have a local view (on the patient), and do neither require nor maintain a central authority that interferes through hierarchical instructions. For this reason, we deem MAIS as an appropriate alternative for supporting the PSP. In particular, MAIS are considered to be suitable for real-world problems that have a special need for flexibility and adaptively to dynamic changes (Mageshwari and Grace Mary Kanaga, 2012).

A Multi-Agent Information Systems Approach to Patient Scheduling

The central artefact for a decentralized PSP is a novel coordination mechanism that allows for local decisions of the decentralized entities, i.e., the units in the hospital as well as the patients. Local decisions address the problem of distributed decision making. The artefact will be instantiated with the help of a multi-agent based information system. As indicated above, MAIS offer characteristics which fit the requirements of building schedules in a hospital. The instantiation of the novel coordination mechanism with the help of a MAIS leads to a prototypical information system which supports a decentralized scheduling approach.

This approach has the potential to be more efficient and responsive than existing scheduling approaches. We will exemplify our novel coordination mechanism later by comparing it against a First Come First Served. According to (Mageshwari and Grace Mary Kanaga, 2012), this scheme is an appropriate initial representation of the standard practice of allocating patients to hospital units.

Agent Framework

We model units in the hospital and patients as agents. Units are rooms, machines and personnel. Interaction happens locally only, i.e., between resource agents and patient agents. Resource agents only see the patients that wait for a treatment at their unit. Patients see their path, i.e., the next units which are individually scheduled for treatment. Patient agents interact with the next unit in a patient's path. They place bids to resource agents in order to get access to the resource. The utilized coordination mechanism will then determine which patient gains access to the requested resource. Depending on the result of an examination or treatment, the path can be changed. If one resource dominates the schedules of one or more other resources, only the dominating resource is modelled as a resource agent. Thus, in most cases, a treatment station (clustered in units) is represented by a single agent.

If there was only one single patient in the system or at each unit, coordination would be trivial and no resource conflicts could occur. If two or more patient agents attempt to access to the same resource at the same time, a coordination mechanism is required. In our approach, we support the case of local coordination, i.e., every resource agent is responsible to coordinate the access of the respective patient agents. There is no central instance or global coordination mechanism. Moreover, the local coordination mechanism has to absorb unplanned treatments like emergencies and patients with higher medical priorities when generating a useful schedule of the resources.

We adopt an exchange-oriented market-mechanism for the coordination among patient and resource agents since these mechanisms allow local, distributed coordination with a low communication overhead. Only capacity- and price-surrogates for treatments are communicated which are relevant. All other information remains private to the respective agents (Wellmann et al., 2001).

Our market exchange participants are the respective software agents. They act autonomously and self-interested. We assume rational behaviour, i.e., patient agents are willing to pay for a faster treatment when negotiating on resources. In order to model the utility function of the agents, we incorporate the health status (severity and criticality) of patients into the patient agents. This health state dependent utility will serve as a currency surrogate. Since no patient agent will accept a treatment which worsens its status without adequate compensation, the achieved resource allocation moves towards a pareto-optimal solution (Varian, 1995; Paulussen et al., 2003; Vermeulen et al., 2006).

Coordination Objects

In this subsection, we will provide further information about the modelled agents and their realization. Patients and resources do pursue different objectives. Thus, they have conflicting goals. Patient agents try to minimize their stay time in the hospital (including all treatment and waiting times) whereas resource agents try to minimize their idle time in order to utilize their capacity. A single criterion value function allows the participating agents to accept changes in the negotiated schedules in order to reach a better global solution. Since healthcare institutions have been established and maintained to help people, our approach is taking a patient perspective. This is in line with the Hippocratic Oath of medical doctors who are supposed to act always for the good of their patients. Thus, we will describe the model of patient agents first, before we will outline the properties of the resource agents.

Patient Agents

One key element in our MAIS are patient agents that model the behaviour of a patient during his/her examination and treatment. Patients can only see their own schedule. Thus, patient agents store the path of the planned examinations and treatments including respective path dependencies, i.e., the order of treatments. The path can change during the treatment, e.g., when new insights occur during examinations or treatments. Furthermore, patient agents contain a utility function for their negotiation. This function is realized as an opportunity cost function, i.e., a regret function that agents intend to minimize. To this end, the task of a patient agent is to book the required examination and treatment time slots for its represented patient.

The opportunity cost function of a patient is not based on monetary values in order to grant access to resources independent of the patient's financial situation. In such a setting, rich patients could overrule poor patients in critical health states. Thus, we chose the patient's health state as a surrogate of an opportunity cost function. However, it is harder to quantify and compare two health states as well as to represent them in a measurable normalized form. In order to overcome this problem, the measurement for severity and criticality has to be determined by the treating medical doctors in a hospital. We adopt the usage of existing utility-based approaches to measure health-related states (Pedroni and Zweifel, 1990; Petrou, 2003; Torrance et al., 1987, Knaus et al., 1985). Such a cardinal measurement is important for inter-agent communication. The utility can be compared between agents and transferred based on the cardinality measurement of the health-related function. In real life, health state cannot be transferred between different patients. In our MAIS, the agents solely transfer health state (utility) for calculating overall better solutions, e.g., solutions that balance reduced waiting times in the light of an increase of the patient's health state and a better resource utilization of the treatment units.

In order to schedule the required resources for examinations and treatments, the health status of a patient is per se not sufficient. Instead, the expected health state progress over time is considered to be more appropriate. This health state progress (or criticality) indicates the decrease of the patient's health in the absence of treatment. For instance, a patient with a relatively good overall health status but a rapidly declining health curve should be prioritized over a patient that has a lower overall but non-critical health state which remains constant.

Determining the cardinal measurement of health state progress will be conducted by applying the concept of *years of well being* (Torrance 1987). This concept models the change of health over time by relating an absolute state of health=1 over a time period xT to a state of health H for a specific period of time T. Following (Torrance 1987), this results in

$$1T \times H = xT \times 1 \Leftrightarrow H = x \quad \text{(Equation 1)}$$

This allows us to relate changes of a patient's health state to a time period.

Obviously, the primary goal of patients in a hospital is to increase their health state through examinations and, accordingly, treatments. Thus, a disease is considered as a disutility for the patient, which adds up over time as long if the illness is not cured. Based on this observation, the opportunity cost *k(t)* for not treating the disease is the difference between the state of health after treatment z and the health state over time *H(t)*. To this end, we modelled the cost function as following:

$$k(t) = \int_0^t z - H(\tau)\, \mathrm{d}\tau \quad \text{(Equation 2)}$$

An important criterion for patient agents in order to monitor their behaviour is the change of the health state. One can think of different characteristics, like linear, exponential, or logarithmic decrease of the health state depending on the illness. As an example, assume a linear decrease, i.e., $H(t) = s - bt$, where an initial health state s is decreased over time controlled by parameter b. Parameter a is the difference between the initial health state s and the expected health state after treatment z. Calculating the opportunity costs, i.e. the change in the health state, we state

$$k(t) = \int_0^t z - H(\tau)\, \mathrm{d}\tau = at + \frac{b}{2}t^2; a = z - s \quad \text{(Equation 3)}$$

Figure 1 shows the relation between the health decrease rate and the opportunity costs. A linear decrease leads to quadratic opportunity costs. By understanding the health state progress as criticality, the priority of a patient increases over time, if $b > 0$.

To be applicable in the field, two aspects need to be addressed. The first one focuses on the specification of the health state progress function of the patient. The second one deals with adapting the respective health care function at later points of the treatment.

- Since the literature poses the existence of specific health functions for different diseases (cf. Petrou, 2003; Torrance et al., 1987), the MAIS can offer pre-defined health state progress functions for the medical doctor in charge. The functions will be offered through a drag-and-drop menu to the medical doctor who can select an appropriate function during his/her examination. Based on the selection of the function, the parameters a (severity) and b (criticality) can be derived. Alternatively, a medical doctor may not be offered a mathematical function, but rather a finite set of pre-defined and labelled values for the health state a and the decrease rate b . Out of this set of values, the physician can then select those pairs with the highest fit to the patient under treatment. For example, a severity a of 0.5 with a criticality b of 0.001 reflects a "suffering patient with urgent need of treatment" ("suffering", "urgent"). A severity a of 0.25 with a criticality b of only 0.0001 represents a "not-suffering, stable patient" ("comfortable", "stable").
- The assessment of the patient on the basis of a selected or approximated health state progress function can be modified any time due to a reassessment of the physician. As the introduced cost function determines the priority of the patient compared to other patients, it is obviously possible to add an "acceleration" factor for more wealthy – but not necessary less healthy – patients, increasing the severity and/or criticality in order to prioritize private patients. For ethical reasons, we disapprove this approach. Technically, the MAIS will ask the medical doctor whether the severity a and criticality b have changed in the meantime and to which magnitude the health state of the patient has been improving or worsening. Based on the entered level of magnitude by the physician, the MAIS will automatically re-adjust the parameters a and b.

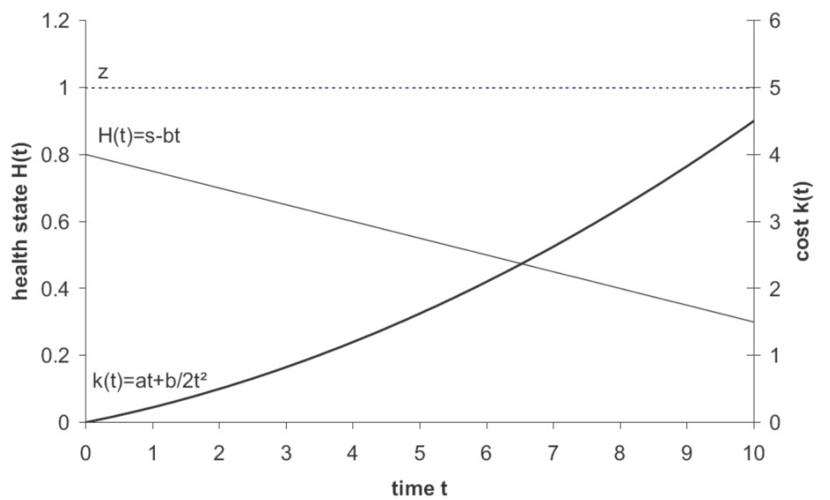

Figure 1. Linear Reduction of Health State

For the handling of stochastic treatment times, the distribution of the durations has to be taken into account. For illustration purposes, we suppose a normal distribution, resulting in the following equation.

$$k(t) = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\tau-\mu)^2}{2\sigma^2}} \left(a\tau + \frac{b}{2}\tau^2\right) \mathrm{d}\tau = a\mu + \frac{b}{2}(\mu^2 + \sigma^2) \quad \text{(Equation 4)}$$

These functions allow the patient agents to negotiate with other patient agents for time slots. As a regulation of the market, priorities can be offered to patients which would encounter losses of their maximal reachable health. New insight from treatments may change the health state function of a patient. The computation of the resulting proxy-prices will be explained when we present the coordination mechanism below.

Resource Agents

Resources in the hospital are represented and coordinated by resource agents in our framework. Their main goal is to minimize idle time and maximize utilization. This is similar to resources in other settings like industrial scheduling, for instance.

In order to reach their objectives, resource agents rely on a cost function. The opportunity cost function depends on the reservation price, which determines the price charged for a reservation of the resource for a time period t. Based on this, incentives for patients can be established, e.g., lower prices for idle times or higher prices for times where additional working hours have to be planned.

In our framework, agents interact in order to establish a schedule: patient agents have to bid for resource utilization at resource agents. In this vein, the health state of a patient agent is related to the value of the required resource. This requires some calibration where the patient waiting time has to be related to the idle time of the resource. Thus, for expensive resources, a higher waiting time has to be accepted.

Coordination Mechanism

The coordination mechanism determines the way how resources get allocated on a patient's medical pathway. Patient agents bid for resources towards resource agents. We will describe the phases of our coordination mechanism more in detail below. The basic philosophy underlying our coordination mechanism is that the overall solution will improve as long as two agents are willing to trade and exchange resources. This is a result from the fact that the overall utility is the aggregated utility of all agents and agents will not increase their utility based on lowering other agent's utility – at least not without compensation (Varian, 1995; Paulussen et al., 2003; Vermeulen et al., 2006).

As indicated, the modelled patient agents compete with each other. For instance, patient agent A may accept a worse schedule for his path, if another patient agent B offers a compensation. This can be of mutual benefit, if the increased utility for B is higher than the opportunity costs of A. Thus, even the distributed setting can increase the overall utility. Resource agents try to maximize their utilization. The overall goal, i.e., a high utilization of hospital resources and the minimization of patient waiting time are realized by the individual goals of patient and resource agents which attempt to find better solution in order to satisfy these goals.

In contrast to a classical auction where typically the best or second-best bid wins, we chose the agent where the sum of counter bids is the lowest. This means, assigning the resource to this agent has the least effect to all the other agents in the auction. As the agents – per definition – reveal their opportunity costs, the single auctions subsume the pairwise exchanges of time-slots between the bidders. As the agent which causes the lowest opportunity costs for the other agents wins, the resulting solution moves towards a Pareto-optimal allocation (c.f. also (Varian, 1995)).

In addition, resource agents can dynamically adapt prices in order to realize incentives for patient agents and to allocate a resource in a time slot with idle times. Moreover, increased prices can prevent allocation of resources in times where additional costs may arise. If a patient agents bids in a number of auctions and wins more than one resource, the resource is chosen where the compensation (opportunity costs of the losing patient agents) is the lowest.

We will now describe the coordination from the perspective of a resource agent. Patient agents bid for resources that are subsequent on their path. This may be a single resource but in some cases patient agents have a choice and can place bids at different resource agents. Our coordination mechanism follows four phases.

1. Subscription phase: patient agents inspect their path. They register at all resource agents that are the next potential subsequent unit in their path using a directory service, e.g., yellow pages.

2. Announcement phase: when a resource agent opens an auction and accepts bids, all patient agents are notified that have registered themselves in the subscription phase.

3. Bidding phase: patient agents can place their bid for the resource.

4. Award phase: the coordination mechanism propagates the winner of the auction by the above described metric (minimum sum of counter-bids). If the winner has also won other auctions and does not need the resource, the resource agent is notified and can assign the next patient agent.

Prioritization can be integrated into the coordination by adding an opportunity cost factor, which determines the effect of the rescheduling. Basically, this is the sum of the opportunity costs of all patient agents that are affected by the rescheduling. Emergencies are integrated into the scheduling by simply delaying the next initialization phase, i.e., not opening an auction but scheduling the resource for the emergency. Thus, emergencies are comparable to disturbances, being captured by the robustness of the proposed mechanism. In contrast, highly critical patients, with urgent need for treatment, are represented by a "regular" patient agent with a corresponding opportunity cost function.

As long as $b>0$, the price a patient agent is willing to bid for a time slot increases over time, avoiding patient agents to wait for ever. However, we recommend to define a threshold for the individual patient waiting time which ensures a reasonable treatment time for every patient.

After a patient agent has access to a resource, the examination or treatment can occur. As indicated above, there is no global view on the path a patient agent takes. Moreover, the changes that can occur on the path after a treatment or examination is not propagated to other agents. If a schedule with longer lead times is required, e.g., for some valuable resource like an operating room, this can be integrated into the resource agents. The realization of the coordination mechanism is conducted according to different variations (i.e., deterministic/stochastic service times; single/multiple resources, emergencies, and priorities).

Example Scenario

As an example, consider the case where two patients compete over a time slot of one resource. Patient 1 has an initial health state of a_1=*0.5* and a reduction rate of health b_1=*0.001*. Patient 2 has also an initial health status of a_2=*0.5* but no reduction rate, i.e., b_2=*0.0*. Let us consider two cases.

In the first case, patient 1 requires *120* minutes of the resource and patient 2 *90* minutes. In this context, we do not assume any variance (which can model the dynamics of treatment). The patients bid their estimated loss value minus their win value. This can be calculated based on the opportunity costs (cf. Equation 3). Obviously, the best case for patient 1 is waiting for his treatment time (*120* minutes) instead of waiting for patient 2 (*90* minutes) plus *120* minutes. The bid is calculated as follows:

$$a_1(\mu_2 + \mu_1) + \frac{b_1}{2}(\mu_2 + \mu_1)^2 - \left(a_1\mu_1 + \frac{b_1}{2}\mu_1^2\right)$$

$$0.5(90 + 120) + \frac{0.001}{2}(90 + 120)^2 - \left(0.5\times 120 + \frac{0.001}{2}\times 120^2\right) = 59.85$$

For patient 2 the bid is exactly 60.

$$a_2(\mu_1 + \mu_2) + \frac{b_2}{2}(\mu_1 + \mu_2)^2 - \left(a_2\mu_2 + \frac{b_2}{2}\mu_2^2\right)$$

$$0.5(120 + 90) - (0.5\times 90) = 60.00$$

Thus, patient 2 wins the auction.

In the second case, we solely change the standard deviation of the resource reservation time of patient 2 to σ_2 = 20.0. As a result, patient 1's bid price is increased to *60.05*:

$$a_1(\mu_2 + \mu_1) + \frac{b_1}{2}((\mu_2 + \mu_1)^2 + \sigma_2^2) - \left(a_1\mu_1 + \frac{1}{2}\mu_1^2\right)$$

$$0.5(90 + 120) + \frac{0.001}{2}((90 + 120)^2 + 20^2) - \left(0.5\times 120 + \frac{0.001}{2}\times 120^2\right) = 60.05$$

We were able to indicate that the bid of patient 2 does not change with respect to its standard deviation. Thus, patient 1 wins in this case. (Paulussen et al., 2003) discusses in detail how stochastic schedules, e.g., variance in treatment time, are calculated.

Implementation

The evaluation of a MAIS requires an implementation of the agents and an infrastructure, where agents can interact by exchanging messages. We implemented our MAIS with the Java Agent Development Platform (JADE) for a molecular intervention environment in which patients with oligometastases are treated. The term oligometastases describes an intermediate state of cancer spread between localized disease and widespread metastases (Corbin et al 2013). The Mannheim Molecular Intervention Environment (M^2OLIE) will start its experimental operations theatre during summer 2014. Later on, it is planned to build and operate an entire molecular intervention centre.

Software agents are implemented as Java objects. This allows simulating concrete scenarios between agents (patient and resource agents). For the initial evaluation of the coordination mechanism, we realized the simulation as described above, i.e., patient agents place bids at resource agents. After the negotiation, the health state and the allocation of the resource agents can be determined. A complete scenario is a set of interactions which take place until each patient agent is treated, i.e., when the patient agent's path is empty. After the scenario is finished, the idle times, bidding prices, and allocations can be determined.

Initial Evaluation

In order to provide first evidence and demonstrate the scalability of our approach, we rely on the open shop benchmark problems from (Taillard, 1993). We decided to choose the Taillard open shop benchmark since it is a well known benchmark and, thus, allows comparing results as well as generating experiments that allow to assess scalability. In the used benchmark problems the number of jobs equals the number of resources, where each job has exactly one task at each resource with a given duration. The sequences of the tasks are open. All jobs can start at the same time. Given this test-layout, our mechanism scales quadratic with the problem size.

Although benchmarks are suitable for comparing different approaches, they do not reflect the dynamics in the application domain. In our case, emergencies and stochastic treatment duration (i.e., a deviation from the resource usage time the patient agents negotiates to the actual time the treatment endured) are important factors for the schedule. In order to investigate the feasibility of our approach, we compare it to a *First Come First Served* (FCFS) strategy which reflects a standard practice of human schedulers in hospitals (Mageshwari and Grace Mary Kanaga, 2012). Since it is the objective of this paper to conceptualize the coordination mechanism which is deemed as the core artefact in our research, we intend to provide first evidence from our simulations. Later, we would like to adopt our approach for the molecular intervention environment as mentioned above.

In the first scenario, we compare the idle times between our multi-agent based approach and a FCFS strategy. For each test, the inter-arrival time of the patients is uniformly distributed between one and ten minutes, arriving until the 300th minute. Each patient receives up to five medical tasks with a duration between 10 and 60 minutes. These tasks are assigned with equal probabilities across six ancillary units.

The computed idle time is the idle time of the patients, i. e. the time a patient is waiting for experiencing the next activity. Figure 2 shows the difference between the two approaches. Except for one outlier, the auction based approach performs better.

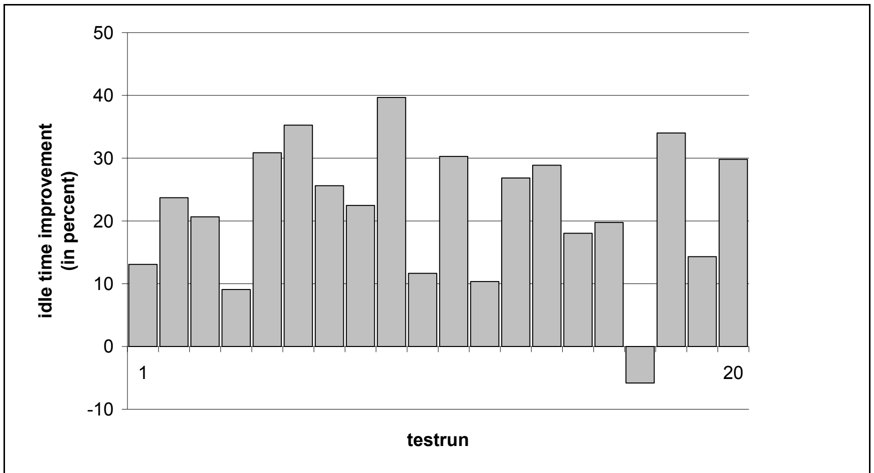

Figure 2. Difference in idle time between auctions and FCFS with no emergencies and no standard deviation from mean duration

In the next scenario, we investigate emergencies. Figure 3 shows the difference between FCFS and Auction based scheduling when rate of 10% emergencies is introduced. Emergency patients can arrive until the 600th minute and each emergency patient receives one task randomly assigned to one of the six ancillary units, which is started immediately. Again, the multi-agent based approach reduces the idle time compared to the FCFS approach.

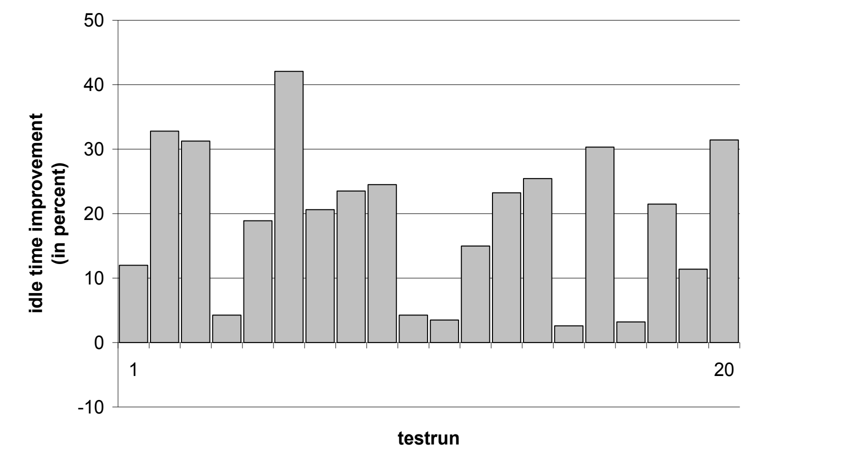

Figure 3. Difference in idle time between auctions and FCFS with 10% probability of emergencies and no standard deviation from mean duration

The next aspect we investigated was the effect of variations in the treatment duration. Figure 4 shows that the MAIS approach produces again smaller idle times than FCFS. We modelled the change in duration time by a stochastic process that can vary the duration with the standard deviation, based on the previous test layout.

We did a comprehensive set of evaluation runs where we looked at different probabilities of emergencies as well as different probabilities of the standard deviation from the mean duration. The interested reader is referred to (Paulussen, 2006) where the complete set of our evaluation can be found. In a nutshell, these evaluations indicated evidence that of the auction based approach yields promising results compared to FCFS with respect to the idle times.

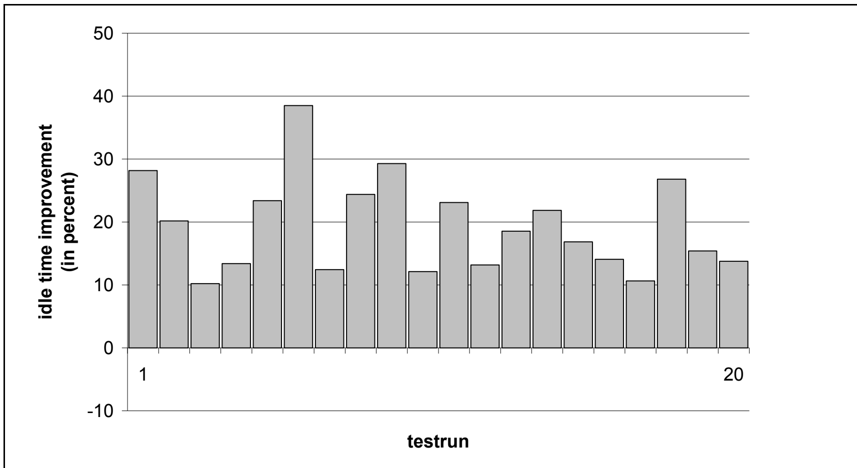

Figure 4. Difference in idle time between auctions and FCFS no emergencies and 10% standard deviation from mean duration

Conclusion and Future Work

We presented a novel approach to the patient scheduling problem in hospitals. Based on the distributed nature of patient scheduling, we have chosen a MAIS approach which instantiates an exchange-based coordination mechanism. Patients are modelled as patient agents that know their own medical pathway including the next treatment or examination units. They negotiate with other patient agents and resource agents in order to gain access to required resources. Our approach provides the opportunity to consider emergencies as well as to integrate priorities. We indicated that the MAIS approach is feasible in general. Furthermore, we demonstrated that it yields better results than FCFS as a common scheduling strategy in hospitals.

To our knowledge, this is the first approach that employs a MAIS approach which captures the whole pathway of a patient's treatment instead of single stations. Since it has been the intention of this paper to focus on the concept of the coordination mechanism as a key artefact, we limited ourselves in diving deeper into the evaluation experiments. Beyond this paper, we investigated additional scenarios where deterministic vs. stochastic scheduling, variations in service time, single and multiple resources, priorities and emergencies are compared to FCFS (Paulussen, 2006). The required information for modelling the agents is potentially available in hospitals, though its extraction from hospital information systems requires comprehensive efforts. Nevertheless, an implementation without changing the hospital's organizational structure and infrastructure is considered to be feasible.

In the near future, we plan to implement our approach within the IT-platform of the M²OLIE experimental operations theatre in order to test and benchmark our system in the field, i.e., to compare the results achieved with other scheduling approaches on the basis to real world data. Furthermore, we plan the integration of mobile devices in our MAIS as front-end technology. Patient agents, for instance, will be supported by Android apps on mobile devices and room tablet computers which are located at the patient's beds – depending on the device restrictions of the hospitals. The coordination mechanism is then used between the agents on tangible devices and not in simulation. Both future trajectories will be subject to a Design Science approach (Hevner et al., 2004).

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