Agent-based Modelling for Simulating Patients Flow in a Community Hospital

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Abstract: One of the most innovative tools in health care informatics is agent-based modelling. Such models change dynamically and help to understand interactions in complex systems especially when simulating competitive and cooperative behaviors in human systems. In our approach we use multi-agent modelling for simulating and evaluating patients flow in a community hospital. The model proposed in this context consists of three different types of agents: the hospital agent, the unit-agent and the patient-agent. Calculation of waiting times was performed using previously collected data from elective patients entering the community hospital ambulance. Poisson distribution was used to model waiting times. The simulation was carried out using the JAVA-based multi-agent-modelling environment Quicksilver. After solving convergence problems, we found, that the simulation especially for the ambulance entrance unit did show completely unexpected results. We were able to prove that the waiting times did not solely refer to the service times of the modelled units. To assure an unobstructed patient flow, we also showed that the mean service time at the entrance unit should not exceed 25 min. Although no evidence was given by the isolated analysis of waiting times, the simulation gave hints for a "hidden patient queue", which after presenting the results in the quality circle meeting was confirmed by the ambulance staff.

1 INTRODUCTION

Waiting times for elective (non-urgent) in- and outpatient hospital treatment are a major health policy concern generating dissatisfaction of patients before their treatment has started. A recent study from the Kopanong Hospital, South Africa found waiting times of up to five hours due to bottlenecks at the reception and the treatment areas (Nhlapo, 2012).

Additionally, waiting times are also economic factors which may cause extra costs and loss of utility (Olukotun and Ogbadu, 2013).

Especially in hopitals with interdisciplinary ambulances which act as an interface in the patient flow of different departments (i.e. surgery, internal medicine) the managing of the clinic wait is an important quality of care challenge (Rondeau, 1998).

To describe and optimize the process of patients waiting in a hospital, methods of stochastic queuing theory show possibilities for hospitals to optimize clinical pathways of patients in time (Brahma, 2013; Schwierz et al., 2011). A mathematical analysis of waiting times of elective patients in a previous study (Ostermann et al., 2003) found a good qualitative agreement with the theoretically assumed results of waiting-times-distribution. Within this theoretical model, six homogenous groups of patients were identified and their total waiting times were calculated ranging from 24 to 53 minutes in the mean which confirms the results of similar studies (Kadivec et al., 2001; Sonnenberg, 2000).

However, this model did not explain how waiting times of patients emerge and in which way they depend on treatment times in the different units. Moreover, it did not answer the question if there is an interaction of different units within the patient flow in the hospital.

One way of answering these question is the use of simulation techniques to model different types of environments. Especially for patients waiting times, several simulation approaches do exist in the literature. For example, Garcia et al. (1995) presented a simulation model focussed on reduction of waiting time in the emergency room of Mercy Hospital in Miami. Another simulation used complex optimization techniques of operation research to model hospital emergency departments queueing systems (Panayiotopoulos and Vassilacopoulos, 1984).

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This article presents an approach to simulate the waiting process of patients using a combination of queuing theory and agent-based modelling.

Agent-based modelling is a fairly new paradigm in health care information science. Although there is no common definition of what is called an artificial agent, it can be described as an autonomous, social, reactive and proactive entity, with a behaviour predictable by attributing abstractions of anthropomorphic attitudes (i.e. intention, obligation, commitment, choice) to describe its behaviour (Della Mea, 2001). Hence, a multi-agent system is a open system, which may change dynamically, when its agents change their behaviour or interact in special ways. It therefore helps to understand interactions in complex systems especially when simulating competitive and cooperative behaviors in human systems, which are difficult to capture in other mathematical formalisms (Bonabeau, 2002). Thus, agent-based modeling has become a powerful simulation technique that has seen a number of applications in the last few years.

In the health care sector, first attempts of using multi agent systems concentrated in the scheduling of operations especially in the field of organ transplants (Moreno et al., 2001; Becker et al., 2003). Meanwhile several applications have demonstrated the power of agent based models in health services research (Maglio and Mabry, 2011). A first attempt to use agent based modeling for hospital management simulation was presented by Sibbel & Urban (2001).

In our approach we used multi-agent modelling for simulating and evaluating patients flow in a community hospital. The main question in our approach is, whether the process of patients' flow itself induces the waiting times or if interactions outside this process may be responsible for the generation of waiting times. Therefore, we carried out a simulation based only on the arrival times and the service times distributions in the particular units. On this bases we compared empirical waiting times with the results of the multi-agent simulation.

2 MATERIAL AND METHODS

The model proposed in this context consists of three different types of agents: the hospital agent, the unit-agent and the patient-agent (Figure 1). The hospital agent represents the hospital and is the models' root. Here patients arrive and are sent to the "Outpatient office"-unit. The time of the patient's arrival is determined by empirical data derived from (Ostermann et al., 2003) given in Figure 2. With this distribution a timetable is created which also defines the exact times of arrival of the patient. As soon as it is time for a new patient to appear, he is created by the hospital agent. The patient's type and his time of arrival are determined.

The unit-agent describes a unit during the admission. In this entity the units outpatient office, radiology, ECG, admission-unit and departments are described. The first four units are transient, since a patient can be sent to another unit after passing this one. The unit-agent holds two queues, one for the patients waiting and one for the patients being treated.

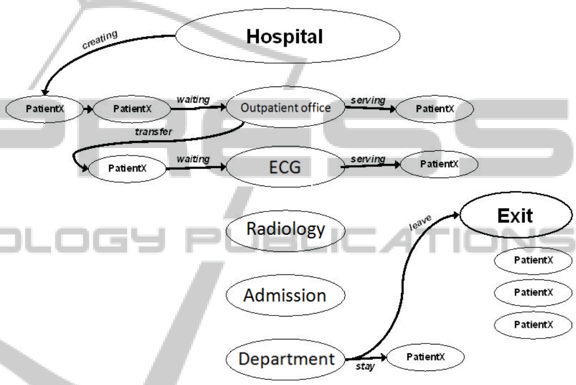

Figure 1: Interacting Agents of this Model.

At every moment there is exactly one patient being treated. Each unit i is associated with a lambda-value λ_i, which is the reciprocal of the mean service time at this unit:

$$\lambda_i = 1/T_i$$

It is derived from the empirical data given in Table. 1 and generates an exponential distributed service time, from which an individual patient's service time is randomly assigned.

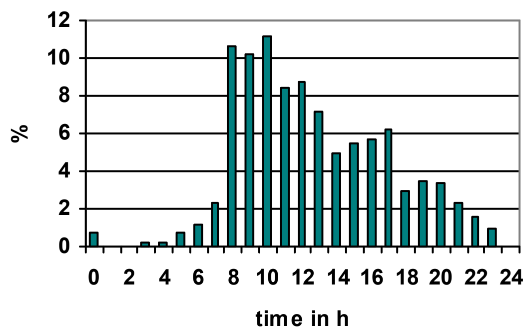

Figure 2: Empirical distribution of patients-arrivals during the day measured for ten days.

The unit-agent also sends the patient to the next unit, as soon as his treatment is completed. For this purpose, it is necessary to find out, whether the patient has to visit another unit. This can be decided by the patient's type and the units he has already been sent to.

If the patient does not have to go to another unit, he is inserted in the queue of treated patients and it is decided whether he is hospitalized or discharged.

When a patient enters a unit, he is appended to the end of the queue of already waiting patients unless he is an emergency patient. Such patients are treated as an exception and hence they are inserted at the beginning of the queue. The time he has to wait until his treatment begins, is measured and stored into the patient-agent.

Table 1: Mean service times for the units.

Unit	Waiting time (mean ± sd)	N
Outpatient office	29.2 ± 18.7	320
ECG	11.4 ± 8.7	89
Radiology	9.7 ± 7.9	197
Admission	9.2 ± 9.2	44
Department	25.8 ± 18.3	68

The patient-agent in this model is an agent without any methods for acting individually i.e. skipping a unit. Similar as in real life, he is sent from unit to unit and just remembers his times of being treated and of waiting. Each patient belongs to a special type. This type specifies, whether the patient is to be treated as an emergency, whether he is a patient with or without transient units or if he needs an inpatient or an outpatient treatment. The distribution of the types was taken from the empirical data of (Ostermann et al., 2003) and is shown in Table 2.

Table 2: Groups of patients and their characteristics.

Group of patients	N	%	$\overline{T}_{min}$	$\overline{T}_{max}$
Stationary patients directly transferred to a hospital department	35	12,2%	37,4	37,4
Stationary patients with one intermediate unit	27	9,4%	40,9	46,6
Stationary patients with two intermediate units	40	13,9%	47,8	53,5
Stationary patients with more than two intermediate units	56	19,4%	*	*
Ambulant patients with one intermediate unit	97	33,6%	24,5	27,9
Ambulant patients with two or more intermediate units	13	4,5%	31,4	31,4

The simulation was carried out using the JAVA-based multi-agent-modelling environment Quick-silver (Burse, 2000). Calculation of waiting times were performed using SPSS with a Poisson-distribution

$$W(t) = 1 - e^{-\lambda t}$$

W(t) expresses the possibility of being served after t minutes.

3 RESULTS

For this evaluation forty patients were simulated, arriving at the hospital during a whole day from 0.00 h to 23.59 h. One minute is the smallest interval in the model, since the empirical data also measure time in minutes. Astonishingly, with the original lambda values for the service times at the entrance unit "Outpatient office" the model did not converge, which means that after finishing one simulation patients still were waiting at the entrance.

Therefore, simulations for different lambda-values were made, with the value of lambda varying from slightly bigger to slightly smaller than the empirically quantified lambda. To further reduce uncertainty, ten days with different initializations of the random numbers were simulated for each lambda-value. Figure 3 shows the convergence of the model depending on the chosen lambda.

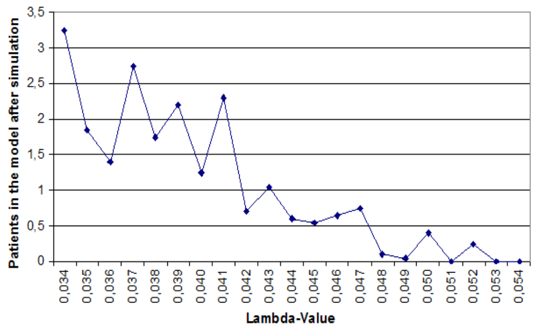

Figure 3: Convergence of the model depending on the chosen lambda for the service time at the entrance unit.

For $\lambda \geq 0.054$ the simulation did finish within the day, thus, in the following, we compared the empirical data with the simulation data for $\lambda = 0.054$ for the entrance unit "outpatient office", which is equivalent to a mean service time of 19 minutes.

Especially for the "Radiology"-unit but also for the "ECG"-unit, patients' waiting-times were sufficiently reproducible by the given service times with the chosen multi-agent system. Simulated and empirical data are given in Fig. 4 and 5.

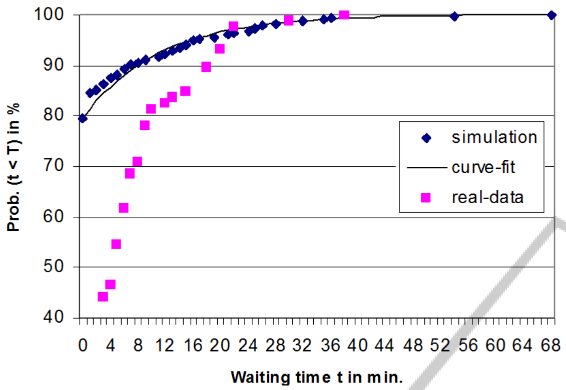

Figure 4: Empirical and simulated waiting times for the "ECG"-unit.

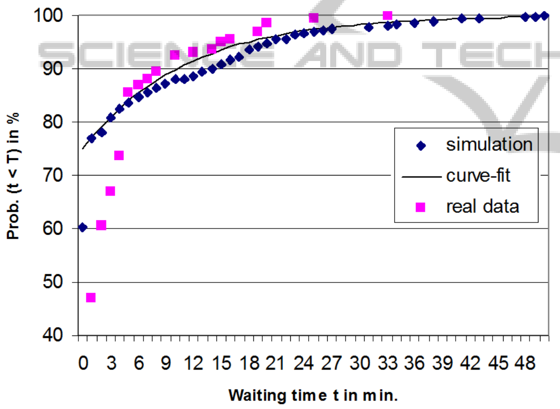

Figure 5: Empirical and simulated waiting times for the "Radiology"-unit.

However, this agreement of simulation and empirical data did not apply for the service times in the outpatient-unit. The empirical mean service-duration in the outpatient-unit was approx. 29 minutes, which lead to a lambda-value of 0.034. This value as already stated did not lead to a converging simulation of the patient flow. It wasn't until a lambda-value of 0.08 when the simulation did show sufficient similarities with the empirical data. The best agreement was found with a lambda of 0.09, which denotes a mean service time at the outpatient office of 11 minutes.

Thus, as a result, we found that the waiting times are not solely generated by service times. Especially for the ambulance unit, there have to be hidden underlying processes beyond treatment which explain the difference of 18 minutes between the empirical measures mean service time of 29 minutes and the fitting simulation result of 11 minutes.

One possible process which induces virtual waiting time is sketched: The patient enters the ambulance. Maybe due to misplacement, his file has to be fetched from another unit a new file has to be created. This will take some time whilst this patient occasionally leaves the ambulance and the next patient is served. Soon afterwards, the patient queues again and is followed up after the actually served patient.

In the empirical study, the patient has included this interruption process into his serving time, which by definition lasts until he is directed to the next unit. Unfortunately, this event has not been part of the model and thus was not reproduced in the simulation.

4 CONCLUSIONS

Originally coming from the social science, agent-based modelling is an innovative technique currently used to simulate patient flows and patient scheduling in hospital environments (Kirn et al., 2000; Lettkemann et al., 2002; Paulussen et al., 2003; Kanagarajah et al., 2008).

We aimed to show the possibilities of a combination of mathematical queuing theory and agent-based-modelling for the analysis of waiting times in the setting of an interdisciplinary hospital ambulance with different units visited by elective appointed patients. After solving the convergence problem of the simulation, we were quite surprised, that the simulation especially for the ambulance entrance unit did show completely unexpected results. One reason for fluctuations in the results might be the certainty and the stability of the model, which is questionable, as different starting values for the random number generator led to non-negligible variations in the simulations.

Despite these structural problems of the simulation, we could prove that the waiting times did not solely refer to the service times of the modelled units. To assure an unobstructed patient flow, we also showed that the mean service time at the entrance unit should not exceed 25 minutes.

Although no evidence was given by the isolated analysis of waiting times, the simulation gave hints for a "hidden patient queue", which after presenting the results in the quality circle meeting was confirmed by the ambulance staff.

For further research the implementation of a patient satisfaction function is a reasonable enhancement of the proposed model. Empirical studies like those carried out by Spaite et al. (2002) found high correlations between the decreases in waiting time intervals and improvement in patient satisfaction. From the mathematical point of view this correlation can be modelled by using a logistic regression model, where the satisfaction s is a function of the waiting time t (Hackl and Westlund, 2000):

$$s(t) = \frac{1}{1+e^{-ct}} \quad ; \text{t = waiting time.}$$

The parameter c models the patients reactivity on waiting and is randomly assigned to the patient agent which cumulates the waiting times t_i of each station. Thus, some patient will show a bad temper after waiting only a short time at one unit whilst others will keep their head although they have high waiting times at all units (Pruyn and Smidts, 1993). If then an individually assigned threshold value i.e. s=0.7 is passed, this could prompt the patient agent to file a complaint to the hospital. Since the incoming complaints increase, this leads to quality measures to lower the service times at the units by increasing the lambda-values. This would lead to a model with a feedback loop, which can be used to simulate special scenarios like queuing of elderly patients (Andersson et al., 2011).

Apart from the analysis of waiting times, such models can also provide useful insights when being used e.g. to simulate patients' drug compliance and behaviour in outcome studies. Such a system for planning, management and decision support of clinical trials has recently been proposed by Heine et al. (2005).

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