AN AGENT-BASED DECISION SUPPORT SYSTEM FOR HOSPITAL EMERGENCY DEPARTMENTS*

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Abstract: Healthcare operational management provides many areas where modelling and simulation have been shown to be useful tools, and within this field there is probably no area more fluid or dynamic than hospital emergency departments (ED). This paper presents the results of an ongoing project that is being carried out by Individual Oriented Modelling (IoM) research group of the UAB, with the participation of Hospital ED Staff Teams. The general objective is creating a simulator that, used as decision support system (DSS), aids the heads of the ED to answer both, "what if..." questions in order to make the best informed decisions possible, and more complex questions involving the optimisation of the system. The defined ED model is a pure Agent-Based Model, formed entirely of the rules governing the behaviour of the individual agents which populate the system. Two distinct types of agents have been identified, active and passive. Active agents represent human actors, meanwhile passive agents represent services and other reactive systems. Active agents are described by Moore state machines extended to include probabilistic transitions. With the aim of verifying the proposed model a simulation has been created using NetLogo.

1 INTRODUCTION

Healthcare is one of the most important services in modern civilisation. In a hospital there are many complex, independent, but interrelated departments (Decker, 1998). The Emergency Department (ED) may well be one of the most complex and fluid healthcare systems that exists, consuming a large portion of economic budgets for health services. However, patients often feel neglected and that the service is saturated.

The simulation of complex systems is of considerable importance and is used in a broad spectrum of fields such as engineering, biology, economy and health care. There are no standard models to describe these complex systems, but they may share many common traits. Agent-Based Modelling (ABM) is an efficient and well utilised technique that has many advantages, amongst them is increased detail in simulation based experiments, a transparent learning process, and the ability to a control and easily modify individual behaviour.

This paper presents the results of an ongoing project that is being carried out by Individual Oriented Modelling (IoM) research group of the UAB, with the participation of the ED Staff Team of the Hospital of Sabadell. Its general objective is create a simulator that, used as decision support system (DSS), aids the heads of the ED to allow additional knowledge of patient admission scheduling (Hutzschenreuter et al., 2008), physician staff (Jones and Evans, 2008), resource optimisation, and decreased patient waiting time (Laskowski and Mukhi, 2008).

Following Macal and North (2006), and also making use of the considerable expertise existing within the IoM research group, a concrete and continuous development methodology has been devised for the construction of the tool, following an iterative & spiral process. Each cycle involves 5 phases: 1) system analysis; 2) model design; 3) simulator implementation; 4) simulator execution and results analysis; 5) simulator validation. Once

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the first iteration has been completed, based on the conclusions obtained during the analysis and validation phase, the model is updated and a new cycle is carried out. The process will be repeated until the objectives are achieved.

An Agent-Based Model for Emergency Departments is being designed, in which all rules within the model concern the agents, no higher level behaviour is modelled; it emerges as a result of local level actions and interactions. This model describes the complex dynamics found in a hospital ED, representing each individual and system as an individual agent. After ending the first cycle two distinct kinds of agents have been identified, active and passive. Active agents represent the individuals involved in the ED, in this case all human actors, such as patients, nurses or doctors. Passive agents represent services and other reactive systems, such as the information technology (IT) infrastructure or central services used for performing tests.

In order to simulate the model state machines are used to represent the actions of each agent and the communication between agents. This takes into consideration all the variables that are required to represent the many different states that an individual may be in throughout the course of their time in a hospital emergency department, be that individual a patient, a member of hospital staff, or any other role. The change in these variables, invoked by an input from an external source, is modelled as a transition between states. The communication between individuals is modelled as the inputs that agents receive and the outputs they produce, both implicitly and explicitly. In order to control the agent interaction, the physical environment in which these agents interact also have to be modelled, being sufficient do it as a series of interconnected areas, such as admissions, the waiting room, or consultation suits.

In the next cycles new agents and state variables will be added gradually, until the simulator behaves as similar as possible to the real system, although being less complex. After this, data assimilation and optimisation techniques will be used for new improvements of the tool. Parallel simulations with different parameters will be performed, in order to make adjustments to the model based on the comparison of the results of these simulations with data from real systems. High Performance Computing will be necessary due to the high amount of data and computation inherent to these both phases.

The remainder of this article is organised as follows; section 2 describes the related work in healthcare operational management and simulation. The proposed emergency department model is detailed in section 3, while the corresponding simulation is given in section 4. In section 5 the future work is pointed out. Finally, section 6 closes with conclusions.

2 RELATED WORK

The modelling and simulation of hospital emergency departments sits at the intersection of a number of distinct fields. In addition Agent-based techniques have been used in the modelling of healthcare operational management, but there are few pure agent-based models to be found in the literature that have been rigorously validated against their real world counterparts.

Economics, biology, and social sciences are the three fields in which agent-based models are most utilised (Jones and Evans, 2008). Modelling techniques using agents can bring the most benefit when applied to human systems where agents exhibit complex and stochastic behaviour, the interaction between agents are heterogeneous and complex, and agent positions are not fixed (Bonabeau, 2002). In the particular case of social sciences ABMs are used in situations where human behaviour cannot be predicted using classical methods such as qualitative or statistical analysis (Norling and Sonenberg, 2000). Human behaviour is also modelled with ABMs in the fields of psychology (Smith and Conrey, 2007) and epidemiology (Epstein, 2009) amongst others.

Agent technology is a useful tool when applied to healthcare applications. Previous works modelling healthcare systems have focused on patient scheduling under variable pathways and stochastic process durations, the selection of an optimal mix for patient admission in order to optimise resource usage and patient throughput (Hutzschenreuter et al., 2008). Work has been performed using differing degrees of agent-based modelling for evaluating patient waiting times under the effects of different ED physician staffing schedules (Jones and Evans, 2008) or patient diversion strategies (Laskowski and Mukhi, 2008).

This proposal addresses many of the issues surrounding the modelling and simulation of a hospital emergency department using agent-based technologies. The basic rules governing the actions of the individual agents are defined, in an attempt to understand micro level behaviour. The macro level behaviour, which means the system as a whole, emerges as a result of the actions of these basic building blocks, from which an understanding of the reasons for system level behaviour can be derived as shown Staindsby, Taboada and Luque (2009).

3 EMERGENCY DEPARTMENT MODEL

The Emergency Department model defined in this work is a pure Agent-Based Model, formed entirely of the rules governing the behaviour of the individual agents which populate the system. Through the information obtained during interviews carried out with ED staff at the Hospital of Mataro and the Hospital of Sabadell, two kinds of agents have been identified; these are active and passive agents. The active agents represent people and other entities that act upon their own initiative (patients, companions of patients, admission staff, sanitarian technicians, triage and emergency nurses, staff emergency doctors, specialists, and social workers). The passive agents represent systems that are solely reactive, such as the loudspeaker system, patient information system, pneumatic pipes, and central diagnostic services (radiology service and laboratories).
This section is dedicated to describe the various components of the general model in detail. Section 3.1 explains the manner in which active agents are modelled. Passive agents are discussed in section 3.2. The communication model is defined in section 3.3. Finally in section 3.4 the details of the environment where the agents move and interact are outlined.

3.1 Active Agents

Active agents are described by state machines, specifically Moore machines. A Moore machine has an output for each state; transitions between states are specified by the input. Considering this, the current state of an active agent is represented by a collection of "state variables", known as the state vector (T). Each unique combination of values for these variables defines a distinct state. In each time step the state machine moves to the next state as defined by the current state and the input vector as described below.

3.1.1 State Variables

In order for the state machine to function, all state variables must be enumerable in some manner. This may be discrete variables or variables representing continuous quantities which have been divided into ranges.

An initial set of state variables has been defined through the round of interviews performed, based on the minimum amount of information required to model each patient and member of staff. Such state variables are: *name/identifier* (for identifying each individual), *personal details* (any individual information which is important in relation with his stay in the ED, such as age, medical history, origin, etc.), *location* (the area of the ED where the individual currently is), *action* (what the individual in a particular state is doing), *physical condition* (haemodynamic-constants and the degree of dependence following the Barthel Index), *symptoms* (healthy, cardiac/respiratory arrest, severe/moderate trauma, etc. Information reported by the patient, and classified by ED staff following the relevant triage and acuity scale, the Canadian or the Andorran scale, depending on the country of the Hospital), *communication skills* (The time spent during the process depends on the agent's ability to communicate. The possible values are low, medium or high), and *level of experience of the ED staff* (None, low, medium or high), which also influences the processing time. Some of the state variables will have a potentially very large set of possible values, e.g. the symptoms or physical condition.

3.1.2 Inputs, Outputs & State Transitions

Upon each time step the state machine moves to the next state. This may be another state or the same one it was in before the transition. The next state the machine takes is dependent on the input during that state. The input may be more accurately described as an input vector (I) that contains a number of input variables, each one of which may take a number of different values. As this is a Moore machine, the output depends only on the state, so each state has its own output, although various states may have outputs that are identical.

Table 1: State transition table.

Current state / output	Input	Next state / output
S_0 / O_0	I_0	S_1 / O_1
S_0 / O_0	I_1	S_1 / O_1
S_0 / O_0	I_2	S_k / O_k
.	.	.
.	.	.
.	.	.
S_x / O_x	I_0	S_y / O_y
S_x / O_x	I_1	S_z / O_z
.	.	.
.	.	.

Again, the output is more accurately described as an output vector (O), a collection of output variables, each with a number of defined possible values. Transitions between states are dependent on the current state at time t (St) and the input at time t (It). Following the transition the state machine will be in a new state (St+1). The state machine can be represented as a state transition table, as shown in Table 1, where each row represents a unique state input combination, showing the output and the state in the next time step (defined by the current state and the input).

3.1.3 Probabilistic State Transitions

In dynamic and complex systems such as hospitals, there exists the necessity for a model not to be entirely deterministic. In these cases a state machine can be modelled with more than one possible next state given a current state and input combination. Which transition is made is chosen at random at the time of the transition, weights on each transition provide a means for specifying transitions that are more or less likely for a given individual. Each one of the input variable of the input vector (I) may take a number of different values. In these cases the state transition table is defined with probabilities on the "effect" of the input. An agent in state S_x receiving input I_a may move to either state S_y, state S_z, or remain in the same state, with a probability of p_1, p_2, and p_3 respectively. One of these transitions will always occur, which is to say $p_1 + p_2 + p_3 = 1$. Figure 1 shows the three different transitions for the "current state-input" combination of this specific example.

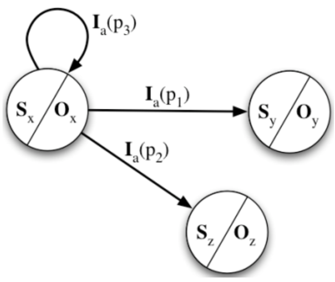

Figure 1: Probabilistic state transitions graph representation.

The exact probabilities may be different for each agent, in this way agent behaviour can be probabilistically defined external to their state, representing personality characteristics in different people.

3.2 Passive Agents

Passive agents represent services within the hospital system such as the IT infrastructure that allows patient details to be stored, radiology services and other laboratory tests as well as specialist systems such as the pneumatic tube networks that some larger hospitals use to quickly transfer samples from one part of a building to another.

Not all passive agents are modelled using state machines. In some cases this may be overly complicated, due to systems with register like memory capacities; in others a simple store and forward messaging system is sufficient.

3.3 Communication Model

To model the interaction between agents 3 types of communication are proposed:

- 1-to-1 between two individuals;
- 1-to-n is representing an individual addressing a group;
- and 1-to-location a type of communication where an individual speaks to all occupants of a specific area, for instance using a speaker system.

Messages contain three parts. The message source is the individual who is communicating, speaking in many cases. The message destination would then be to whomever this individual is speaking to, and thirdly the content, what is being said. These three parts form the message tuple (<src>, <dst>, <content>). In the case of a 1-to-location message, the destination of the message is an entire location, so the content may need to include the actual indented recipient of the message. This could represent a patient's name being called over the loudspeaker system.

3.4 Environment

All actions and interactions modelled take place within certain locations, collectively known as the environment. The environment itself can be defined to different levels depending on the positional precision required of the model.

The environment in which the agents move and interact is passive and discrete. There is little distinction made between agents in the same location. A patient in the waiting room does not have any more specific sense of position than they are in the waiting room. Certain locations may be physically distinct, but functionally identical, for instance there are usually a number of triage rooms,

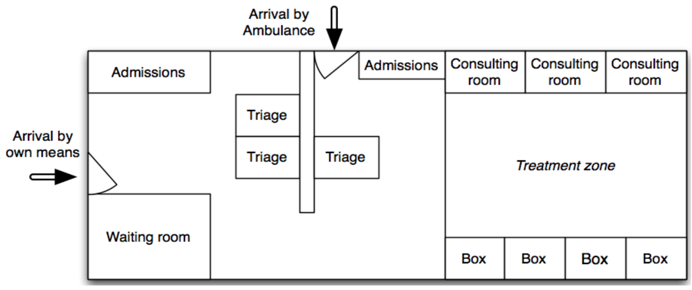

Figure 2: Simplified Emergency Department layout.

an agent in any one of these will act as if they are in any triage room, however they Simplified ED layout are distinct in order to represent that each available room may only be used by one nurse-patient group at a time.

The environment also contains representations of the relative distances between different discrete locations. Figure 2 shows a representation of topographical distribution of the Emergency Department.

4 SIMULATION

With the aim of verifying the proposed model against real data sets from a hospital emergency department a simulation has been created using the agent based simulation tool NetLogo (Wilensky, 1999).

The tool initially uses a simplified set of patient attributes and a less complicated patient flow in order to make a preliminary demonstration of how accurate a simulation can be produced using only reduced parameters. The four primary areas are accounted for: admissions, triage (3 boxes), waiting rooms (one for patients before triage, and the second for patients who have passed the triage process, and are waiting for treatment), and diagnosis and treatment areas conjoined (that include four boxes). The types of individuals represented in this simulation are patients, admission staff, triage nurses, and doctors.

Figure 3: Simulation display in NetLogo.

In this model the patients are shown following the same path through the ED, even though in reality they are been treated differently depending on the level of severity of their condition. The time spent at each stage may also represent laboratory tests, which are not shown explicitly.

Since a primary use of the simulation tool is to garner feedback from the professionals who work in emergency departments, a graphical representation of the process is considered a very important aspect of the simulation. NetLogo allows visualisations of agent actions and interactions; a sparse patient load is shown in figure 3.

There is further validation to be performed. However initial tests using the simulation are showing very promising results.

5 FUTURE WORK

Following the iterative & spiral process discussed in the introduction, after this first cycle, the work will continue with the purpose of improving the model and the simulation, applying assimilation techniques for that.

In the next iterations new agents and state variables will be added gradually, until the simulator behaves as similar as possible to the real system, although being less complex. After this, parallel simulations with different parameters will be performed, in order to make adjustments based on the comparison of the results obtained in these simulations with data from real system.

Once the improving of the model achieves a proper adjustment level, simulation will be used as DSS, with the objective of answering "*what if...*" questions in order to aid healthcare managers make the best informed decisions possible. The tool will let to divine what will happen to the system as a whole if one or more changes are made to the parameters that define it. After additional definitions of quantitative and qualitative indices, more complex questions involving the optimisation of the system could be evaluated. In these specific cases simulation will be carried out with the objective of minimising (patient waiting times, total service cost, etc) or maximising (patient's satisfaction) indices, subject to specific constraints of human and material resources available.

The distribution pattern of patients' arrival to the ED varies among the day, but also over a week or a year. For this reason, and having into account the objectives of the project, is desirable to run simulations for an annual period of time. In addition, as a result of the potential number of individuals to include in the simulation and the number of states in the state machine of each individual, a great amount of values should be computed. Considering also the parallel simulations that will have to be performed during the adjustment process, it can be concluded the need of using High Performance Computing.

6 CONCLUSIONS

A concrete example of an Agent-Based Model for Hospital Emergency Departments has been presented, which represents a hospital ED following system analysis performed at a number of different hospitals, under the advice of healthcare professionals with many years of experience. The model uses state machine based agents which act and communicate within a defined environment, providing the ability to study the dynamic of complex systems without the difficulty of obtaining exhaustive system descriptions required by other modelling paradigms. An initial simulation has been created in order to demonstrate the validity of the model.

Future improvements of the model will be made using data assimilation and optimisation techniques. The former will involve performing parallel simulations with different parameters, and after comparing data from simulation and real system, making the proper adjustments of the model. The latter refers to optimisation through simulation runs in order to minimise or maximise indices such as patient waiting times, total service cost or patient satisfaction, while adhering to constraints in the number of doctors, nurses and hospital beds available. In both parallelisation and High Performance Computing will be necessary.

From this point, the simulation will be able to be used as the core component of a decision support system to aid hospital administrators make better use of resources, achieving a more efficient and improved patient care cycle. This in turn will allow better management of dynamic patient flow, either as a result of specific circumstances or seasonal fluctuation.

REFERENCES

Bonabeau E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. In *Proceedings of the National Academy of Sciences*.

Decker K, Li J., 1998. Coordinated Hospital Patient Scheduling. In: *Proceedings of the 3rd International Conference on Multi Agent Systems. Washington, DC, USA: IEEE Computer Society;*

Epstein J. M., 2009. Modelling to contain pandemics. In *Nature,* 460(7256):687.

Heath B, Hill R, Ciarallo F., 2009. A Survey of Agent-Based Modeling Practices In *Journal of Artificial Societies and Social Simulation*;12(4):9.

Hutzschenreuter A. K., Bosman P. A. N., Blonk-Altena I., van Aarle J., La Poutr´e H., 2008. Agent-based patient admission scheduling in hospitals. In: *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems. Richland.*

Jones S. S., Evans R. S., 2008. An Agent Based Simulation Tool for Scheduling Emergency Department Physicians. In: *AMIA Annual Symposium proceedings,*

Laskowski M., Mukhi S., 2008. Agent-Based Simulation of Emergency Departments with Patient Diversion. In: *eHealth*; p. 25–37.

Macal C., and North M., 2006. "Tutorial on agent-based modeling and simulation part 2: how to model with agents," In: *Proceedingsof the Winter Simulation Conference,* pp. 73 – 83.

Norling E., Sonenberg L., Ronnquist R., 2000. Enhancing Multi-Agent Based Simulation with Human-Like Decision Making Strategies. In: *MABS*; p. 214–228.

Smith E. R., Conrey F. R., 2007 Agent-Based Modeling: A New Approach for Theory Building in Social Psychology. In: *Pers Soc Psychol Rev*. 11(1):87–104.

Stainsby H., Taboada M., Luque E., 2009. Towards an Agent-Based Simulation of Hospital Emergency Departments. In: *Proceedings of the 2009 IEEE International Conference on Services Computing. Washington, DC, USA: IEEE Computer Society*

Wilensky U., 1999. NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University Evanston, IL.