Optimization of Healthcare Emergency Departments by Agent-Based Simulation

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Abstract

This paper presents an Agent-Based modeling and simulation to design a decision support system (DSS) for the operation of Healthcare Emergency Departments (ED). This DSS aims to aid EDs managers in setting up strategies and management guidelines to optimize the operation of EDs. This ongoing research is being performed by the Research Group on Individual Oriented Modeling (IoM) of CAOS in the University Autonoma of Barcelona (UAB) in close collaboration with Hospital ED Staff. The simulation main objective is to optimize the performance of such complex and dynamic Healthcare ED. Optimization is performed to find the optimal ED staff configuration, which consists of doctors, triage nurses, and admission personnel, i.e. a multidimensional problem. Two different indexes, to minimize patient waiting time, and to maximize patient throughput, were proposed and tested and their results obtained applying an exhaustive search technique, yield promising results and better understanding of the problem.

Keywords: Optimization, healthcare operational management, emergency department, agent-based simulation, decision support systems

1. Introduction

At the present time, healthcare systems have become large, complex, and very dynamic environments, particularly Emergency Department (ED). ED is a sui generis unit of hospitals. It is open and functioning 24 hours a day, 365 days per year. Typically, ED patients could arrive by walking, or by ambulance, and they undergo a triage, which determine the acuity of their condition assigning them a priority level. Patients with threatening disease, i.e. high priority level, are treated almost immediately by a physician compared to those patients with less severe injuries. Then, an initial diagnosis and treatment is proposed, and patients could be admitted into the service or discharged. EDs have high demand of service, which increases their cost, and they generally operate with limited healthcare resources and budget. In the decade leading up to 2006 in the USA, ED visits (patients) have increased by 32%, whereas the number of EDs have decreased by 4.6%, and the number of visits per person increased by 18% [1]. Also, in Spain between...
2001 and 2007, the visits to EDs have increased by 23.2% [2]. Over half of those visits to EDs are nonurgent and could be treated in alternative healthcare settings. Overcrowding of EDs is a worldwide problem, and as a consequence of such situation, waiting time increases, affecting quality and speed of care [3]. Despite EDs are under those huge, and growing demands they suffer several budget cuts. Nevertheless, such critical ED service must be satisfied with the best quality as quickly as possible. An obvious solution to this problem is to increase the capacity of EDs. Such capacity is limited by the size of the healthcare facility and the available staff, which includes physicians, nurses, admissions, and services personnel. However, such straightforward solution is not the best approach, and could be unrealizable. Healthcare system heads must maximize, for example, the use of healthcare resources, in order to minimize patient waiting time and increase patient satisfaction, whereas being constrained by limited budget.

This paper presents the results of an ongoing research project that is being carried out by the Research Group in Individual Oriented Modeling (IoM) in the University Autonoma of Barcelona (UAB), with the participation of the ED head team of the Hospital of Sabadell in Cataluña, Spain. The general objective of the project is to develop a simulator of ED’s operation that, used as a decision support system (DSS), could help the heads of EDs to set up strategies, and management guidelines to enhance the performance of such EDs. As a first step to towards this goal, the main objective of this work is to propose a simple but realistic simulation model to represent the operation of EDs, in order to study their optimum performance under certain operational and economical conditions. The mathematical formalism of the latter is a multidimensional optimization problem which can be stated by equation (1):

\[
\begin{align*}
\max / \min \quad & f(X) \\
\text{subject to} \quad & x \in C
\end{align*}
\]

where \( f : C \rightarrow \mathbb{R} \), and \( f(X) \) at any \( X \in C \) cannot be evaluated exactly, and must be estimated via a simulation procedure by assuming that \( X \) is discrete, global sampling from \( X \) is possible. The goal is to identify the staff members of EDs that optimize its performance, taking into account the complexity of EDs and their optimum expected performance needs to be estimated via simulations. However, optimization via simulation is a difficult problem [4], as simulations are usually computationally expensive, i.e. even estimating \( f(X) \) at a single point \( X \in C \) in equation (1) may require substantial effort. Consequently, only few alternatives can be explored.

Herewith, the ED is modeled by an Agent-Based Model (ABM), in which all rules within the model concern the involved agents (in our case the doctors, triage nurses and admission personnel, and the patients), no higher level behavior is modeled. The system behavior emerges as a result of local level actions and interactions [5]. This model describes the complex dynamics found in an ED, representing each individual and system as an individual agent. 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 and ED staff (admission staff, nurses, doctors, etc). Passive agents represent services and other reactive systems, such as the information technology (IT) infrastructure or services used for performing tests. State machines are used to represent the actions of each agent. This takes into consideration all the variables that are required to represent the many different states that such individual (a patient, a member of hospital staff, or any other role in the EDs) may be in throughout the course of their time in a hospital emergency department. The change in time of these variables, invoked by an input from an external source, is modeled as a transition between states. The communication between individuals is modeled 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 has to be modeled, being sufficient to do it as a series of interconnected areas, such as admissions, triage box, the waiting room, and consultation suits.

The remainder of this article is organized as follows; section 2 describes the related works. The proposed emergency department model is detailed in section 3, while the results of initial simulation optimizations are given in section 4. Finally, in section 5 the conclusions and future work are presented.

2. Related works

The interest on simulating healthcare systems is not new, in 1979 computer simulations were applied to hospital systems to improve the scheduling of staff members [6], and in another simulation [7] the aim was to quantify the impact that the number of staff members, and beds had on patient throughput time. Moreover, a survey of discrete-event simulation (DES) in healthcare clinics was presented in [8].
Although discrete-event simulation is widely used in simulating healthcare systems, agent technology is a good option in healthcare applications, since it is better to characterize the operation of complex systems as the EDs are. ABM can explicitly model the complexity arising from individual interactions that arise in the real world. Agent-based simulation allows people to model their real-world systems in ways that either not possible or not readily accommodated using traditional modeling techniques, such as DES or system dynamics [9]. Previous works modeling healthcare systems have focused on patient scheduling under variable pathways and stochastic process durations, the selection of an optimal mix of patient admission to optimize the use of resources and patient throughput [10]. Work has been performed to evaluate patient waiting times under different ED physician schedules, but only one utilized real data [11] and another one patient diversion strategies [12], both using different degrees of agent-based modeling.

There is a relevant article which uses ABM to simulate the workflow in ED [13]. It focuses on triage and radiology processes, but not real data was used, the acuity of patients are not considered, and healthcare providers do not always serve patients in a first-come-first-serve basis.

Simulation optimization is used to improve the operation of ED in [14], using a commercial simulation package, and in [15] the authors combine simulation with optimization, which involves a complex stochastic objective function under a deterministic and stochastic set of restrictions.

Finally, an evolutionary multiobjective optimization approach is used for dynamic allocation of resources in hospital practice [16], while in [17] the authors found that agent-based approaches and classical optimization techniques complement each other.

As stated above, this proposal addresses many of the issues surrounding the modeling and simulation of a healthcare emergency department using the agent-based paradigm, where the efficiency of agents in this area has not been totally explored yet. Basic rules governing the actions of the individual agents are defined, in an attempt to understand micro level behavior. The macro level behavior, that of 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 behavior can be derived [18].

3. Emergency department model

As mentioned above, the Emergency Department model defined in this work is a pure Agent-Based Model, formed entirely of the rules governing the behavior of the individual agents which populate the system. Through the information obtained during interviews carried out with ED staff at 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, admission staff, sanitarian technicians, triage and emergency nurses, and doctors. 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 succinctly. Section 3.1 explains the manner in which active agents are modeled. 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. As described below, in each time step the state machine moves to the next state as defined by the current state and the input vector.

3.1.1. State variables

In order for the state machine to work, all state variables must be enumerable in some manner. These 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 initial set of state variables includes: Name/Identifier, Personal details, Location, Action, Physical condition, Symptoms, Communication skills and Level of experience (ED staff only). Some of these state variables will have a variable and potentially very large set of possible values, e.g. the symptoms or physical condition.
3.1.2. Inputs, outputs & probabilistic state transitions

Upon each time step the state machine moves to the next state. This may be a new state or the same one it was before the transition, as shown schematically in Figure 1. The state machine involves probabilistic transitions, where a given combination of current state and input have more than one possible next state. Which transition is made is chosen at random at the time of the transition, weights on each transition provide the means to specify transitions that are more or less likely for a given individual. The input is more accurately described as an input vector (\( I \)) containing a number of input variables, each one capable of taking several different values with a certain probability. 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. 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. Our state transition table is defined with probabilities on the input as shown in Figure 1b. An agent in state \( S_x \) receiving an input \( I_a \) may move to either one of the states \( S_y, S_z \) 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 \( p_1 + p_2 + p_3 = 1 \). The state diagram would then have three different transitions for that state-input combination as shown in Figure 1a.

![Figure 1: Probabilistic state transition graph and its corresponding table.](image)

The exact probabilities may be different for each agent, in this way agent behavior 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, radiology services, and other laboratory tests as well as specific systems such as the pneumatic tube networks that some larger hospitals use to quickly transfer samples from one part of the building to another one. In some of the passive agents the state machine will be a simple system that interacts with active agents. The model is not, however, purely a state machine. In order to represent data storage or other systems that may have a very large number of combinational states a simple memory model will be used. A passive agent may have (although it is not necessary) a simple record based memory system, allowing it to store and repeat information provided by active agents.

3.3. Communication model

The interaction between agents is carried out through communication. Such communication is modeled as the input that agents receive and the outputs that they produce. Both, inputs and outputs may be explicit and implicit. The communication model represents three basic types of communication: 1) 1-to-1, between two individuals (the message has a single source and a single destination); 2) 1-to-n, representing an individual addressing to a group (like a doctor giving information to patient and nurses during the diagnostic process); and 3) 1-to-location, when an individual speaks to all occupants of a specific area (for instance when any staff member uses the loudspeaker system to broadcast a message to all the people who are in a specific waiting room). Implicit or passive communication also exists, where an agent may be communicating just by remaining in a certain area. This is the manner in which agent
vision, what each agent sees, can be represented using the same model. An agent is continuously emitting messages with regard to its visible physical status and location, other agents receive these 1-to-location messages and may act upon them in certain circumstances. Messages are divided in three parts. The message source is the individual who is communicating. The message destination would then be to whomever this individual is speaking to, and thirdly the content, what is being said. These three parts make up the message tuple \((\text{<src>}, \text{<dst>}, \text{<content>})\). 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 modeled take place within certain locations, collectively known as the environment. The environment itself can be defined in two different levels depending on the positional precision required by the model: at a low or high granularity scale. The former implies to divide the space into a few general areas, where all agents in the same area may freely interact. The second requires more precise positioning, using physical Cartesian coordinates. In the specific case of the Emergency Department it is enough to use a low granularity positioning scale, although it is important to represent distances between distinct areas, to correctly model travel times form one area to another. The different areas identified through the information obtained during the interviews carried out are: Admissions, Triage Box, Waiting Room, diagnostic and treatment zone.

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, an agent in any one of these will act as if they are in any triage room, however the simplified ED layouts 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.

4. Optimization

4.1. Problem description

The simulator for this work is used as a black box as described below, includes simple realistic descriptors of the ED’s: agents, basic physical infrastructure, and operating practices. Nevertheless the more realistic the simulator is, the better results and optimizations are. It is implemented by the agent-based simulation environment NetLogo [19], which is well suited for modeling complex systems such as the EDs. For simplicity, only four different types of active agents are considered: admission staff (A), nurses (N), doctors (D), and patients. The ED staff have two kinds of expertise: low and high, labeled as junior, and senior, respectively. Junior staff will require more time to accomplish their tasks than seniors, which cost-wise are more expensive (see Table 1).

The initial scenario adopted for the experiments is to simulate patients moving through a simplified ED physical infrastructure that includes four primary areas: admissions, triage (up to three boxes), two waiting rooms (one for patients before triage, and the other for patients who have passed the triage process, and are waiting for treatment), and the diagnosis and treatment area (four boxes). The following basic patient attributes were assumed. Patients arrive to the ED by their own, and wait to be attended in the admission area. Then, patients stay in the first Waiting Room (WR1), until a triage nurse call them. After the triage process patients pass to a second waiting room (WR2), and stay there until an available doctor calls them to start the diagnosis, and to prescribe a treatment (which might include laboratory tests) depending on the patient’s symptoms, and physical condition. Finally, patients are discharged from the ED. Such simplified ED layout is shown in Figure 2. Although realistic treatment is based on the acuity of patients, in this initial simulation patients we assumed that patients have the same path throughout the ED. In this experiment a constant pattern of patients arrival pattern has been assumed, since we would like first to work with a simpler model. Also it will be assumed that patients arrive to the ED after a certain time step, and with four different patients arrival probabilities (P) 20, 40, 60, and 80%. Those probability values are used to emulate the randomness of the incoming patients to the ED.
The multidimensional optimization problem considered in this paper aims to find the optimal ED staff configuration under certain operational constrains (the optimal solution will correspond to the minimum value of an index which is defined furtherdown in the application experiments). The dimension of the problem corresponds to: the types and number of ED staff considered, i.e. doctors (D), triage nurses (N), and admissions personnel (A), which could be, as stated above, junior or senior; the working time units considered for each of them, their associated cost units. The assumed values of each of those are shown in the Table 1. This represents a combinatorial or multidimensional problem (where each variable or in this case ED staff member represents one dimension plus the patients arrival, i.e. the input to the ED). Such combinatorial problem is shown in Table 2 for doctors -14 cases- (nurses and admission personnel have similar combinations -9 cases for each of them). Taking this into account specific scenarios or configurations have to be simulated several times, changing parameters to show the effect of considering different probabilities of the patients arrival time, this strategy will allow us to generate set of results from which particular effects can be analized.

Table 1: Staff members with their associated costs, and working time according to their kind.

<table>
<thead>
<tr>
<th>Agent</th>
<th>Cost (£)</th>
<th>Time (ticks)</th>
<th># of Agents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Senior (S)</td>
<td>Junior (J)</td>
<td>Senior (S)</td>
</tr>
<tr>
<td>Doctor (D)</td>
<td>1,000</td>
<td>500</td>
<td>260</td>
</tr>
<tr>
<td>Nurse (N)</td>
<td>500</td>
<td>350</td>
<td>90</td>
</tr>
<tr>
<td>Admin (A)</td>
<td>200</td>
<td>150</td>
<td>20</td>
</tr>
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</table>

Even with this simple setting of an ED the search space is large, i.e. the search space has 4,536 (which results of assuming a combination of two types -junior or senior- of up to 4 doctors, 3 nurses, 3 admissions, and 4 different probabilities of patients arrival, i.e. 14 × 9 × 9 × 4) combinations from which the optimal combination that minimizes the desire index, under some restrictions, will be obtained. In the experiments shown in sections 4.2 and 4.3 the period simulated of the ED operation was of 24 hrs. (which represent 25,000 ticks -NetLogo’s time step- for all the experiments, and an average input of 400 patients, which is the average incoming patients that the heads of ED of the Hospital of Sabadell have reported).

Two different indexes were set in order to evaluate the utility of the Agent-Based ED simulator for optimizing the resources. Exhaustive search technique was used to obtain the optimum in the experiments reported in sections 4.2 and 4.3. All simulations were done using the simulator described previously, using the NetLogo’s BehaviorSpace tool, serially and using an IBM cluster, which has 32 compute nodes with 2 x Dual-Core Intel(R) Xeon(R) CPU 5160...
Table 2: 14 combinations of Doctors (D). Two types of doctors, Junior (J), and Senior (S). DR\textsubscript{i} represents Diagnosis Room \textit{i}.

<table>
<thead>
<tr>
<th>DR\textsubscript{1}</th>
<th>DR\textsubscript{2}</th>
<th>DR\textsubscript{3}</th>
<th>DR\textsubscript{4}</th>
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<td>DJ</td>
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<td>DS</td>
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running at 3.00GHz, with 12 GB of RAM, and 4MB of L2 share cache (2x2).

4.2. First experiment

The first index aimed to minimize patient waiting time in the ED, with cost configuration less or equal to 3,500 €. Thus, the first index is expressed mathematically in equation (2).

\[
\text{Minimize patient waiting time } f(D, N, A) \\
\text{subject to } D_{\text{cost}} + N_{\text{cost}} + A_{\text{cost}} = \text{Cost} \leq 3,500
\] (2)

The results are shown in Figures 3 and 4; where the circle points are the staff configurations that satisfy the restriction, while the triangle points are the minimum for each different case of probability, 20% and 40%, respectively. The minimal configurations are presented in Figures 3c, 3d, 4c, and 4d, as well as their costs.

In Figures 3a and 3c, there are three different staff configurations that have the minimum average waiting time, but with different costs. Also, in the same Figure 3a, it can be appreciated that there are many other staff configurations that are quite close to the minimum time, but less expensive.

In the other cases, where the probability \( P \) of patients arrival increases, i.e. has higher probability of patients arrival, there are only few staff configurations around the minimum, or clearly only one. Not only does the patients arrival increase, but also the minimum average patient waiting time \( (\bar{t}) \), as expected, as well as the cost of the staff configuration, and also the standard deviation \( \sigma_{\bar{t}} \) of the average patient waiting time are shown in Table 3. The number of patients increases at waiting rooms, both WR1 and WR2 (shown in Figure 2) at times t1, t2, t3, and t4 (each time represents every 7,500 ticks of simulation), and finally the number of unattended patients increases as well. In Table 3 all these results are shown. It is noticed when the number of patients arrival probability is higher, i.e. 80%, patients in the waiting rooms increases (shown in Table 3).

Table 3: Results for the best minimum average for each of the four presented scenarios. \( \bar{t} \) represents the minimum average waiting time, \( \sigma_{\bar{t}} \) is the standard deviation, and the variation coefficient is between parenthesis.

<table>
<thead>
<tr>
<th>P</th>
<th>( \bar{t} )</th>
<th>( \sigma_{\bar{t}} ), (coef. var. %)</th>
<th>( \bar{\epsilon} )</th>
<th># attended patients</th>
<th># unattended patients</th>
<th># patients at WR\textsubscript{1} t1, t2, t3, t4</th>
<th># patients at WR\textsubscript{2} t1, t2, t3, t4</th>
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<tbody>
<tr>
<td>20</td>
<td>428</td>
<td>48, (11%)</td>
<td>2850</td>
<td>83</td>
<td>1</td>
<td>0,0,0,0</td>
<td>0,0,0,0</td>
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<tr>
<td>40</td>
<td>514</td>
<td>81.5, (15.9%)</td>
<td>3150</td>
<td>182</td>
<td>4</td>
<td>0,0,0,1</td>
<td>0,0,0,1</td>
</tr>
<tr>
<td>60</td>
<td>790</td>
<td>174.5, (22.1%)</td>
<td>3400</td>
<td>290</td>
<td>8</td>
<td>1,1,0,1</td>
<td>3,2,4,1</td>
</tr>
<tr>
<td>80</td>
<td>3266</td>
<td>1670.4, (51.2%)</td>
<td>3350</td>
<td>294</td>
<td>100</td>
<td>8,19,32,43</td>
<td>12,25,37,51</td>
</tr>
</tbody>
</table>
(a) Average patient waiting time for a $P = 20\%$ of patients arrival.

(b) Average patient waiting time for a $P = 40\%$ of patients arrival.

(c) Staff configurations that have the minimum $\bar{w}_t$ for a $P = 20\%$. They are shown as triangles in Figure 3a.

(d) Staff configurations that have the minimum $\bar{w}_t$ for a $P = 40\%$. They are shown as triangles in Figure 3b.

Figure 3: Average patient waiting times graphs and their corresponding table with the optimal staff configurations. Triangle points are the minimum.

(a) Average patient waiting time for a $P = 60\%$ of patients arrival.

(b) Average patient waiting time for a $P = 80\%$ of patients arrival.

(c) Staff configuration that have the minimum $\bar{w}_t$ for a $P = 60\%$. It is shown as triangle in Figure 4a.

(d) Staff configuration that have the minimum $\bar{w}_t$ for a $P = 80\%$. It is shown as triangle in Figure 4b.

Figure 4: Average patient waiting times graphs and their corresponding table with the optimal staff configuration. Triangle points are the minimum.
4.3. Second experiment

The second index aims to minimize a compound index: \( \text{cost} \times \text{time}, CT \), without any cost restriction. This index is expressed mathematically in equation (3).

\[
\text{Minimize } \text{cost} \times \text{time}(CT) f(D,N,A) \tag{3}
\]

![Figure 5: Results \( y = \text{cost} \times \text{time} \). Triangle points are minimum, and a worthy staff configuration, respectively.](image)

This index was set to test the simulator with a non-simple objective function, as well as to find which ED staff configuration yields the best quality of service, i.e. to maximize patient throughput. The Figure 5 shows all the search space, 16,632 staff scenarios (which results of assuming a combination of two types -junior or senior- of up to 8 doctors, 6 nurses, and 4 admissions, i.e. \( 44 \times 27 \times 14 \)). There are many scenarios that give a good index value, but there are two of them that are the most important, as shown in Table 4.

![Table 4: Two worthy staff configurations that give almost the same quality of service. \( \bar{w}t \) represents the minimum average waiting time, \( \sigma_{w}t \) is the standard deviation, and the variation coefficient is between parenthesis.](image)

Although both staff configurations are almost the same, they have different minimum average waiting time, this is why the first staff configuration label as Best 2, despite its lower cost has a worst minimum average waiting time. Not only the index is different and higher, but its standard deviation of patient waiting time is higher. It is important to notice that a staff configuration a bit more expensive has almost 10% lower variation coefficient of the patient waiting time, as well as almost a third lower index value and minimum average waiting time.

5. Conclusions and future work

A simple but realistic Agent-Based Model to simulate Healthcare Emergency Departments (ED) has been proposed an applied. The main objective of the model is to be used as a tool to help EDs managers in setting up strategies and management guidelines to optimize the operation of EDs. The model takes into account the complexity and dynamic nature of the EDs which are difficult to characterize. The model uses Moore state machines based agents which
act and communicate within a defined layout. The simulations presented here serve to test the model. Two simulation experiments were carried out using real data about the staff configuration and the (minimum) physical infrastructure of a Hospital ED. Two different indexes were set to evaluate the operation of the Agent-Based Emergency Department simulator. Even though the search of the optimum staff configurations analyzed, 4,536 and 16,632 for the first and second experiments, respectively, were performed through an exhaustive search technique (which implies a lot of search time) the results are encouraging, since not only they are as expected (larger and more experienced staff lead to shorter average patient waiting time), but also show interesting results when the waiting time standard deviation is analyzed. Indeed the simulation experiments allowed to understand, and analyze better the problem. However, even with the small problem size analyzed the number of combination is large, as well as the computing time. Moreover, the resources that this problem would demand to perform statistical analysis for longer periods (first to reproduce and then to foretell) are huge. Therefore, a better optimization approach rather than exhaustive search, must be used.

As future work, an alternative methodology scheme for optimization is being devised. This approach consists in finding a continuous function that describes the Emergency Department operation, which is a discrete and multidimensional problem, and through such function will allow us to obtain the optimum, or at least reduce the search space. Thus, getting as a result of doing such an intelligent search will very likely reduce time and computing resources utilized. This scheme would be an intermediate approach between an exhaustive search technique and an heuristic one. Moreover, due to the multidimensional nature of the problem, i.e. large number of individuals, the number of states in the state machine of each individual, and the different time periods, a large number of values should be computed. Therefore, High Performance Computing will have to be used.

References