ABMS OPTIMIZATION FOR EMERGENCY DEPARTMENT

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Abstract

An agent-based modeling and simulation to design a decision support system for healthcare emergency department (ED) to aid in setting up management guidelines to improve it is presented. This research is being performed by the Research Group in Individual Oriented Modeling at the UniversitatAutònoma de Barcelona with close collaboration of the hospital staff team of Sabadell. The objective of the proposed procedure is to optimize the performance of such complex and dynamic healthcare EDs, which are overcrowded. Exhaustive search optimization is used to find the optimal ED staff configuration, which includes doctors, triage nurses, and admission personnel, the amount, and sort of them, i.e., a multi-dimensional and multi-objective problem. Three different indexes were set. The model is implemented using NetLogo. The results obtained by using alternatives Monte Carlo and Pipeline schemes are promising. The impact of these schemes to reduce the computational resources used is described.

In this research a two-phase optimisation methodology for optimisation via simulation for healthcare Emergency Departments is proposed. The first phase is a coarse grained approach consisted in a global exploration step over the entire search space. This phase identifies promising regions for optimisation based on a neighbourhood structure of the problem, using a pipeline scheme approach of an Emergency Department. This first phase returns a collection of promising regions. The second phase is a fine grained approach that consists in seeking the best solu-

tion, either the optimum or a sub-optimum by performing a "reduced exhaustive search" in such promising regions.

1 Introduction

Nowadays, all over the world healthcare systems are facing enough pressure to deal with the increasing demand on service, mainly for the reason that people are living longer, a and budget reduction. However, they have to provide the best care, quality and service. Needless to say, health is one of the most appraised gifts for human beings; therefore, it is crucial to preserve it. Healthcare units were designed to take charge of it. Healthcare systems have evolved during the previous decades, specifically emergency departments (ED). ED is a primary healthcare department, usually the main entrance to the hospital, and a key component of the whole healthcare system. EDs are semi-autonomous units that are open and staffed 24 hours per day, 365 days per year, including holidays. The original mission of EDs is to primarily handle only emergent situations. However, ED visits include a wide range of illnesses and injuries, i.e., truly emergencies, urgent, semi-urgent, and non-urgent cases. EDs have increased their resources to attend all of those cases, becoming large, complex and dynamic units. In spite of such an increase, patients continue to suffer, since they do not have access to ad hoc healthcare, in some cases due to the inefficiencies of the EDs functioning. As a result of this, EDs are overcrowded and the length of stay (LoS) of patients has increased, whereas quality of service has decreased. Indeed, overcrowding of EDs is a worldwide issue, and a national crisis in the US [**?**]. Although ED overcrowding is not a new topic, since it was documented in the literature 20 years ago [**?**], there is not a solution to this long and growing issue yet. Despite that EDs are under this overcrowding phenomena, they have suffered budget reductions. Therefore, new techniques and paradigms should be found in order to deal with such overcrowded condition. ED managers require different and fresh solutions, because society demands not only care, quality and service, but also the best care, quality and service. A direct solution to this issue is increasing the size of EDs. However, this straightforward solution is limited by the facility, number of staff (doctors, nurses, technicians) and services (computing, communication, radiology, laboratory), and it is not the best approach. Also, healthcare managers have to maximize the use of healthcare resources, whereas being constrained by limited budget, in order to minimize patient LoS, while increase satisfaction of the patients, i.e., to optimize the performance of the ED. The resource planning of an ED is complex activity, since it is not linear, and it varies depending on time, day of week and season. The ability to simulate special situations such as seasonal increases in ED demand can be useful for the efficient use of resources. There are no standard models to describe a complex system. Simulation becomes an important tool for modeling systems including many elements as well as interdependencies among the elements, and/or considerable variability. Discrete event simulation (DES), system dynamics (SD) and agent-based modeling and simulation (ABMS) are the three main approaches used to simulate healthcare systems. There are a large and growing body of literature describing the use of DES and SD models in ED studies, but the use of ABMS for this purpose is few; although healthcare systems are based on human actions and interactions that are quite difficult to model with DES, and can be more properly modeled with ABMS.

This article presents the results of a research project that is being carried out by the Research Group in Individual Oriented Modeling (IoM) in the Universitat Autònoma de Barcelona (UAB), with the participation of the ED managers of the Hospital of Sabadell (one of the most important Hospitals in Spain that gives care service to an influence area of 500,000 people, and attends 160,000 patients/year in the ED). The general objective of the project is to develop an ED simulator that, used as a decision support system (DSS), aids the managers of EDs in setting up strategies, and management guidelines to enhance the efficiency of such EDs. The specific objective is to implement in the proposed DSS model an algorithm to optimize the number of staff members of EDs, including admission staff, triage nurses, and doctors, under certain economical and operational constrains.

This work optimises the sanitary staff configuration of an actual ED. The sanitary staff configuration comprises: doctors, triage and emergency nurses, admission personnel, and x-ray technicians, the amount, and sort of them. Staff configuration is a combinatorial and multidimensional problem, that can take a lot of time to be solved. In order to do optimisation, objective functions to minimise or maximise have to be set. Three different indexes were set: minimise patient length of stay (LoS); maximise number of attended patients per day (Throughput); and minimise a compound index, the product of the cost of a given sanitary staff configuration times patient length of stay (CLoS). HPC is used to run the experiments, and encouraging results were obtained. However, even with the simplified ED used in this work the search space is very large, thus, when the problem size increases, it is going to need more resources of processing in order to obtain results in a reasonable time.

A good monitoring system will alert you to issues before they become problems and allow you to focus on your core business and not reacting to IT issues.

The Emergency Department model defined herewith is a pure Agent-Based Model (ABM), and so is formed entirely of the rules governing the behaviour of the individual agents that populate the system. The system behaviour emerges as a result of local level actions and interactions. This model describes the complex dynamics found in an ED, representing each individual and system as an individual agent.

The rest of this article is organized as follows; Section 2 describes the literature review. The ED model is succinctly described in Section **??**, the mathematical-computational model of the ED are presented in Section **??**, the optimization problem of interest, the experiment, and the results of three simulation optimization techniques are given in Section **??**, the proposed methodology to find the optimum is described in Section **??**. Finally, the conclusions and future work are presented in Section 7.

2 Related Work

In 1979 computer simulation was applied to hospital systems to improve the scheduling of staff members [**?**], and in [**?**] the aim was to quantify the impact that the amount of staff members and beds had on patient throughput time. Moreover, a survey of discrete-event simulation in healthcare clinics was presented in 1999 [**?**].

Although, discrete-event simulation is widely used in simulating healthcare systems, agent technology is most suited to be used in healthcare applications, because it characterizes better the operation of complex systems such as EDs. There is a relevant article which uses ABM to simulate the work flow in ED [?]. It focus on triage and radiology processes, but not real data is 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 [?], using a commercial simulation package, and [?] combines simulation with optimization, which involves a complex stochastic objective function under deterministic and stochastic sets of restrictions. Also, in [?] system simulation is used to improve the flow of the ED using an index to measure the degree of congestion of ED. Previous works on modeling 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 optimize resource usage and patient throughput [?]. Work has been performed evaluating patient LoS under the effects of different ED physician staffing schedules, and the only one found until now that utilizes real data is [?] or patient diversion strategies [?]. An evolutionary multi-objective optimization approach is using for dynamic allocation of resources in hospital practice [?], while in [?] it was found that combining agent-based approaches and classical optimization techniques complement each other.

This proposal addresses many of the issues surrounding the modeling and simulation of a healthcare emergency department using agent-based paradigm, where the efficiency of agents in this area has not been totally explored yet. The 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 [?].

3 Healthcare Emergency Department Operations and Their Modelling

3.1 Agent-Based Model of Emergency Department

In this Section, a brief description of the proposed Agent-Based Model (ABM) is presented. The Emergency Department model defined by this work is a pure ABM, thus it is formed entirely of the rules governing the behavior of the individual agents which populate the system, no higher level behavior is modeled. The system behavior emerges as a result of local level actions and interactions. 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. Moore 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) may be in throughout the course of their time in a hospital emergency department. The change in these variables, invoked by an input from an external source, is modeled as a transition between states. In some specific cases the state machine involves probabilistic transitions, where a given combination of current state and input has 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 a means for specifying transitions that are more or less likely for a given individual. Probabilities may be different for each agent. In this way heterogeneity is provided to agents as people, since agent behavior can be probabilistically defined external to their state. The communication between individuals is modeled as the inputs that agents receive and the outputs they produce, both implicitly and explicitly. The communication model represents three basic types of communication. The first type is 1-to-1 communication, such as between two individuals, for instance admission staff and patient, where a message has a single source and a single destination, as well as between patients, or staff personnel. The second type is 1-to-n communication, where a message has a single source and a specific set of recipients, for example when a doctor communicates with both patient and his companion, or when doctor communicates with other doctors and nurses. The last type is 1-to-location communication, where a message has a single source, but it is received by every agent within a certain area or location. This occurs when a triage nurse sends a message to the patients in the waiting room, through the loudspeaker system. In order to control the agent interaction, the physical environment in which these agents interact also has to be modeled, such as admissions, triage box, the waiting room, and consultation suits. A detailed description of the emergency department model using the agent-based paradigm can be found in the following article [**?**]

3.2 Mathematical-Computational Model of Emergency Department

3.2.1 Multi-Objective Optimization

From the mathematical point of view, the optimization problem stated in Section 1 is to optimize the number of staff members of an ED under specific economical and operational constraints. This problem can be formulated as a multi-objective optimization problem which is formally defined as follows: Find the vector $\vec{x}^* = [x_1^*, x_2^*, ..., x_n^*]^T$ which optimizes the vector function:

$$\begin{aligned} \text{max / min} \quad & \vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), ..., f_k(\vec{x})]^T \\ \text{subject to} \quad & g_i(\vec{x}) \leq 0 \quad i = 1,2,...,m \\ & h_i(\vec{x}) = 0 \quad i = 1,2,...,p \end{aligned} \tag{1}$$

where f_i is the $i-th$ objective function. x_i^* is a discrete vector, global sampling of $\vec{x}_i^*$ is possible to get, but not all of $f_i(x_i^*)$ can be evaluated exactly, and must be estimated via a simulation procedure. Since several objective functions exist, instead of looking for a single solution, an acceptable or trade-off solutions it is trying to find them. It is say that a vector of decision variables $\vec{x}^* \in PO$ is *Pareto optimal* if $\nexists$ another $\vec{x} \in PO$ such that $f_i(\vec{x}) \leq f_i(\vec{x}^*) \quad \forall i = 1,...,k)$ and $f_j(\vec{x}) < f_j(\vec{x}^*)$ for at least one j. PO represents the feasible region of the problem, i.e., where the constraints are satisfied. The goal of the optimization procedure is to identify the staff members of the EDs that optimize their performance, which needs to be estimated via a simulation due to the complexity of EDs. Optimization via simulation is a difficult task [**?**]. As simulations are usually computationally expensive, even estimating $f_i(x_i^*)$ at a single point in Equation (1) may require substantial effort, which implies that only some scenarios would be explored. Three different alternatives used in this work are briefly described following.

3.2.2 Exhaustive Search

Exhaustive search (ES) is used for discrete and combinatorial problems in which no efficient solution technique is known. In order to determine the solution it might be necessary to test each possibility and verify if it satisfies the statement of the problem. If there exists a solution, then ES technique will always find such solution. Nevertheless, the computational cost is high and proportional to the number of possible solutions which could be quite large, i.e., a combinatorial explosion.

3.2.3 Pipeline

This technique is usually known as assembly line. It consists of several ordered stages. The output of one stage is the input of the next one. Once the second stage is working, the first stage is attending the next input, and so on. Therefore, when the hole pipeline is full, one output per time is obtained. All stages could be configured to have more than one unit, i.e., parallel stages. So, not only the throughput but also the pipeline of the system is enhanced. However, when the process between each stage cannot be synchronized the use of buffers ought to be necessary. The pipeline time can be expressed by Equation (2), where S_i represents each stage of the pipeline.

$$\text{Pipeline time} \;= \frac{1}{\Sigma \frac{1}{S_1}} + \frac{1}{\Sigma \frac{1}{S_2}} + ... + \frac{1}{\Sigma \frac{1}{S_k}} \tag{2}$$

4 Optimization via Simulation of Emergency Departments

4.1 The Problem

The optimization problem considered in this paper and expressed by Equation (1) aims to find the best ED staff configuration: doctors (D), triage nurses (N), and admissions (A), which optimize the ED's functioning. The simplified patient flow in the ED is defined as follows: Patients arrive to the ED on their own, and waits to be attended in the admission area. Then, patients stay in the first Waiting Room (WR), WR1, until a triage nurse calls them. After the triage process, patients pass to a second WR2, and stay there until a free doctor calls them to begin the diagnosis and treatment phase, depending on the patient's symptoms and physical condition, as well as prescribed tests. At the end, patients are discharged from the ED. Even though realistic treatment is based on the acuity of patients they have the same path throughout the ED at this moment in this research project.

For simplicity, only four different types of active agents are considered: patients, admission staff, nurses, and doctors. Staff considered characteristics are shown in Figure **??** and Table 1. Taking into account: a) that each of the personnel staff has two levels of expertise: low and high, labeled as Junior (J) and Senior (S), respectively. Figure **??** and Table 1 show, as well, the combinatorial problem for admission personnel, nurses and doctors; b) that the Junior staff will require more time to finish their own duty than Seniors; c) Senior staff have higher salaries. The time, and salary of each four staff, and the number of them, from 1 up to 3 or 4, are shown in Table 1. Figures **??**, **??**, and **??**, and Table 1 synthesize the combinatorial or multi-dimensional problem of interest (where each variable or in this case ED staff member represents one dimension, three dimension up to now, plus the patients arrival, i.e., the input to the ED, shown in Figure **??**). As mentioned above the objective is to identify the combination numbers of staff members of ED that optimize its performance. The expected value of the latter needs to be estimated via simulation due to the complexity of EDs (as discussed previously).

4.2 Proposed Optimisation via a Simulation Model for Emergency Departments

5 Applications of the Proposed Optimisation of Emergency Departments via Simulation

The two-phase optimisation via simulation of healthcare Emergency Departments, ED, proposed in **??** was applied herewith to analyse the administrative strategies leading to optimum decisions about the physical and human resources of an ED. In particular, the impact on the economics and the productivity of Sabadell Hospital ED of different sanitary staff configuration (v.gr., doctors, triage nurses, and admission personnel) were analysed. It is a discrete combinatorial optimisation problem.

There are three main issues to be addressed to carry out the evaluation, namely: the *simulation models* that represent the system under study (discussed along the previous chapters); the *decision variables* and *workloads* used as inputs of the simulation models; and the *metrics* used to asses the benefits of the proposal. We have defined some significant workloads and a set of metrics to observe both functional and performance features of the proposal. This set of metrics were defined in term of three different indexes, namely: patient length of stay (LoS) in the ED; number of attended patients per day (Throughput); and a compound index, the product of the cost of a given sanitary staff configuration times patient length of stay (CLoS).

In the following sections, the *decision variables,* the *workloads*, and the *metrics* are described. Finally two case scenarios and their results are presented and discussed.

5.1 Field Information of Sabadell Hospital ED

It was found through interviews with the managers at the EDs of Sabadell hospital (which provides healthcare services to an average of 160,000 patients/year), it was found that a basic sanitary of its ED staff is composed by: doctors, triage nurses, emergency nurses, admission personnel, and x-ray technicians, as shown in 1. This table also shows some characteristics of such sanitary staff, namely: sort of staff as junior or senior (that represents less and more expertise, respectively); their respective costs (euro [1]); the operational patient-service-time (hours); and the minimum and maximum number of each kind of staff.

In reference to the Sabadell Hospital ED incoming patients, an average of four hundred of patients daily arrive to the ED of Sabadell hospital. As example, the statistics corresponding to February 2010, of this real average number of incoming patients and its hourly distribution are shown in 1. As stated in **??** all incomings patients are triaged to identify the acuity of them and to

[1] **It is not an actual euro, could be any currency.**

prioritise their urgency of attention. Thus, the average percentage, according to the priority level of urgency of attention, of the incoming patients to the ED of Sabadell hospital is as follows: triage level 1 - 1%; triage level 2 - 4%; triage level 3 - 20%; triage level 4 - 32%;and triage level 5 - 43%. Patients identified as triage level 4 and triage level 5 represent up to 75% of the total of the incoming patients to the ED of Sabadell hospital.

5.2 Decision Variables of Sabadell Hospital ED

The sanitary staff included in 1 are the *decision variables* of the ED. The disaggregation of 1 yields 2, which includes 9 possible combinations of admission personnel (junior/senior); 3, which also includes 9 possible combinations of triage nurses (junior/senior); 4, that presents the 5 possible combinations of emergency nurse (junior/senior); 5 that shows the 5 possible combinations of x-ray technician (junior/senior); and 6, with 14 possible combinations of doctors (junior/senior) in which the examined cases for each type of staff were included. It is a discrete combinatorial problem.

2 to 6 were ordered by the sort and number of staff, whereas 7 to 11 were ordered by the equivalent operational patient-service time ($\mathbf{t}^*$) of a "single one" sanitary professional (working in parallel) of each sanitary staff configuration (admission personnel, nurses, doctors, and x-ray technicians). This order was obtained by applying the pipeline scheme described in **??** and is graphically shown in 2 to 4. In these figures the index value was represented by colours, the most important values in such figures were the green ones.

In the first example, 2 shows a 3D scattered graph, which axes were ordered by the sort and number of sanitary staff (first column/case number of 2 to 6. In this graph the green points were all scattered, and they shown lack of connectivity. The second example, 3 shows the index value ordered by the cost of the sanitary staff configuration. The green points were less scattered, but blue values and others were mixed, showing a region not totally connected. Finally, the third example, 4, shows the index value ordered by the equivalent operational patient-service time ($\mathbf{t}^*$) of each sanitary staff configuration of 7 to 11. This graph shows a connected and almost "non" scattered green region.

5.3 Workloads

In order to analyse the performance of the ED, the real average four hundred incoming patients daily arrive to the ED of Sabadell hospital was considered as follows. This real input was divided into four scenarios, i.e., four different workload scenarios, up to: 4, 9, 13, and 17 incoming patients hourly, as shown in 12 (i.e., up to 96, 216, 312, and 408, respectively for 24hrs.). These different workload scenarios were used to supply different loads to the ED, whereas the percentage of the priority level of patients was maintained.

Table 1: Sabadell Hospital ED staff and their: associated expertise, costs, operational patient-service time, and number.

Sanitary staff	Cost (euro [1])		Time/patient (hours)		Number of personnel
	Senior	Junior	Senior	Junior	min - Max
Doctor	1000	500	0.26	0.35	***1 – 4***
Triage Nurse	500	350	0.09	0.13	***1 – 3***
Emergency Nurse	500	350	0.14	0.18	***1 – 2***
Admission personnel	200	150	0.02	0.035	***1 – 3***
X-ray technician	200	150	0.09	0.14	***1 – 2***

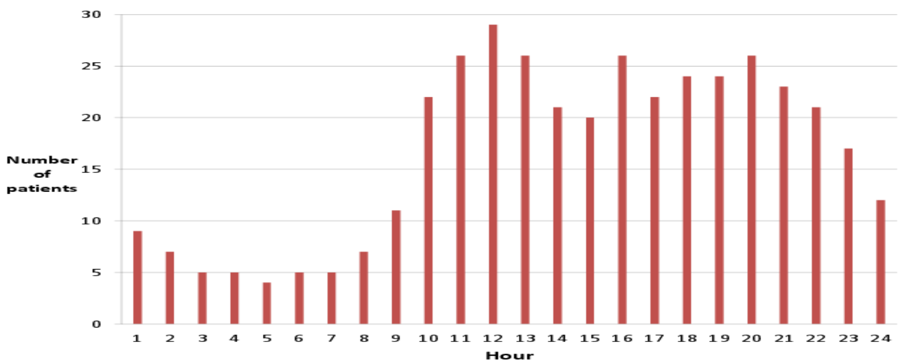

Figure 1: Sabadell Hospital ED average of 400 daily incoming patients and its hourly distribution (February 2010).

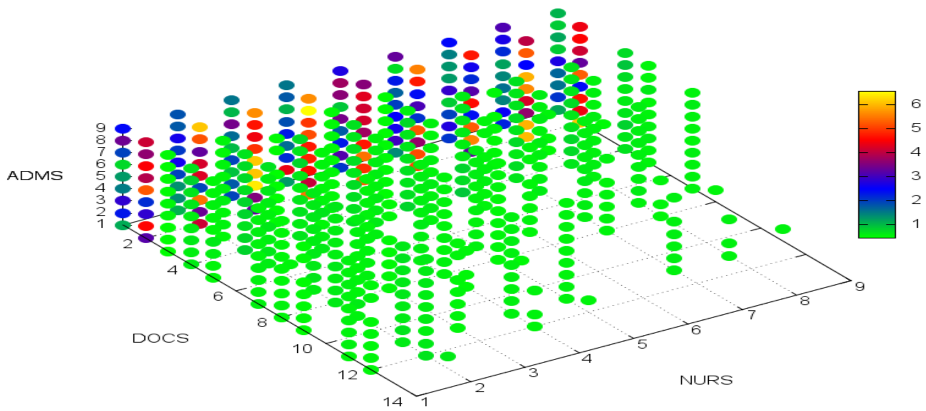

Figure 2: 3D scattered graph ordered by the sort and number of staff 2 to 6. The green values of interest were totally scattered.

Case number	$\mathbf{AD}_1$	$\mathbf{AD}_2$	$\mathbf{AD}_3$
1	AS	-	-
2	AJ	-	-
3	AS	AS	-
4	AJ	AJ	-
5	AS	AJ	-
6	AS	AS	AS
7	AJ	AJ	AJ
8	AS	AJ	AJ
9	AS	AS	AJ

Table 2: 9 Admission (A) personnel cases. ADi is Admission Den$i$.Where AJ means Admission personnel Junior, whereas AS means Admission personnel Senior.

Case number	$\mathbf{TR}_1$	$\mathbf{TR}_2$	$\mathbf{TR}_3$
1	NS	-	-
2	NJ	-	-
3	NS	NS	-
4	NJ	NJ	-
5	NS	NJ	-
6	NS	NS	NS
7	NJ	NJ	NJ
8	NS	NJ	NJ
9	NS	NS	NJ

Table 3: 9 Nurse (N) cases. TRi represents Triage Room i. Where NJ means Triage Nurse Junior, whereas NS means Triage Nurse Senior.

Case number	$\mathbf{ENR}_1$	$\mathbf{ENR}_2$
1	ENS	-
2	ENJ	-
3	ENS	ENS
4	ENJ	ENJ
5	ENS	ENJ

Table 4: 5 Emergency Nurse (EN) cases. ENi represents ENurse Room i. Where ENJ means Emergency Nurse Junior, whereas ENS means Emergency Nurse Senior

Case number	$\mathbf{XR}_1$	$\mathbf{XR}_2$
1	XRS	-
2	XRJ	-
3	XRS	XRS
4	XRJ	XRJ
5	XRS	XRJ

Table 5: 5 X-ray technician (XR) cases. XRi represents X-ray Room i. Where XRJ means X-ray technician Junior, whereas XRS means X-ray technician Senior

Table 6: 14 Doctor (D) cases. DRi represents Diagnosis Room i. Where DJ means Doctor Junior, whereas DS means Doctor Senior.

Case number	$\mathbf{DR}_1$	$\mathbf{DR}_2$	$\mathbf{DR}_3$	$\mathbf{DR}_4$
1	DS	-	-	-
2	DJ	-	-	-
3	DS	DS	-	-
4	DJ	DJ	-	-
5	DS	DJ	-	-
6	DS	DS	DS	-
7	DJ	DJ	DJ	-
8	DS	DJ	DJ	-
9	DS	DS	DJ	-
10	DS	DS	DS	DS
11	DJ	DJ	DJ	DJ
12	DS	DJ	DJ	DJ
13	DS	DS	DJ	DJ
14	DS	DS	DS	DJ

Table 7: Ordering staff configuration of admission personnel according to the equivalent operational patient-service time ($\mathbf{t}^*$) of each staff configuration.

Case number ($\mathbf{t}^*$)	Old case number	$\mathbf{AD}_1$	$\mathbf{AD}_2$	$\mathbf{AD}_3$	**euro**	**Time (hrs)**	$\mathbf{t}^*$ **(hrs)**
1	6	AS	AS	AS	600	0.02	0.007
2	9	AS	AS	AJ	550	0.035	0.008
3	8	AS	AJ	AJ	500	0.035	0.009
4	3	AS	AS	-	400	0.02	0.001
5	7	AJ	AJ	AJ	450	0.035	0.012
6	5	AS	AJ	-	350	0.035	0.013
7	4	AJ	AJ	-	300	0.035	0.018
8	1	AS	-	-	200	0.02	0.02
9	2	AJ	-	-	150	0.035	0.035

Table 8: Ordering staff configuration of triage nurses according to the equivalent operational patient-service time ($\mathbf{t}^*$) of each staff configuration.

Case number ($\mathbf{t}^*$)	Old case number	$\mathbf{TR}_1$	$\mathbf{TR}_2$	$\mathbf{TR}_3$	**euro**	**Time (hrs)**	$\mathbf{t}^*$ **(hrs)**
1	6	NS	NS	NS	1,500	0.09	0.03
2	9	NS	NS	NJ	1,350	0.13	0.033
3	8	NS	NJ	NJ	1,200	0.13	0.04
4	7	NJ	NJ	NJ	1,050	0.13	0.043
5	3	NS	NS	-	1,000	0.09	0.05
6	5	NS	NJ	-	850	0.13	0.053
7	4	NJ	NJ	-	700	0.13	0.07
8	1	NS	-	-	500	0.09	0.09
9	2	NJ	-	-	350	0.13	0.13

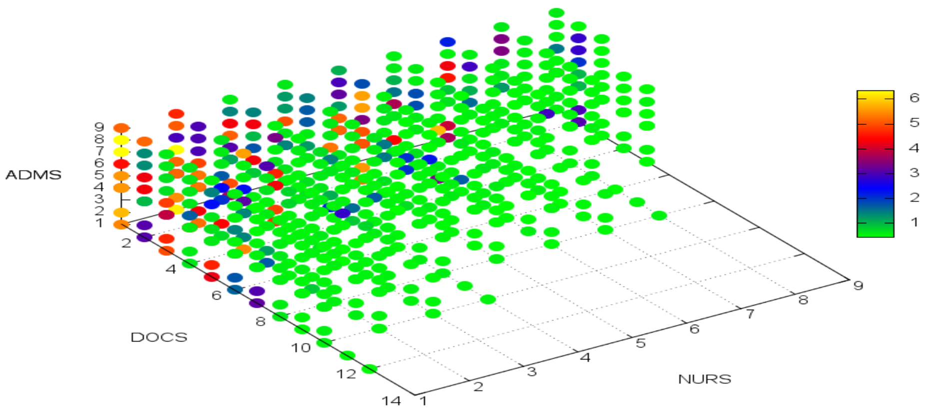

Figure 3: 3D scattered graph ordered by the cost of sanitary staff configuration. The green values of interest were not so scattered, but not interconnected.

Table 9: Ordering staff configuration of doctors according to the equivalent operational patient-service time ($\mathbf{t}^*$) of each staff configuration.

Case number ($\mathbf{t}^*$)	Old case number	$\mathbf{DR}_1$	$\mathbf{DR}_2$	$\mathbf{DR}_3$	$\mathbf{DR}_4$	**euro**	**Time (hrs)**	$\mathbf{t}^*$ **(hrs)**
1	10	DS	DS	DS	DS	4,000	0.26	0.065
2	14	DS	DS	DS	DJ	3,500	0.35	0.069
3	13	DS	DS	DJ	DJ	3,000	0.35	0.075
4	12	DS	DJ	DJ	DJ	2,500	0.35	0.081
5	6	DS	DS	DS	-	3,000	0.26	0.087
6	11	DJ	DJ	DJ	DJ	2,000	0.35	0.09
7	9	DS	DS	DJ	-	2,500	0.35	0.095
8	8	DS	DJ	DJ	-	2,000	0.35	0.11
9	7	DJ	DJ	DJ	-	1,500	0.35	0.117
10	3	DS	DS	-	-	2,000	0.26	0.13
11	5	DS	DJ	-	-	1,500	0.35	0.149
12	4	DJ	DJ	-	-	1,000	0.35	0.175
13	1	DS	-	-	-	1,000	0.26	0.26
14	2	DJ	-	-	-	500	0.35	0.35

Table 10: Ordering staff configuration of emergency nurses according to the equivalent operational patient-service time ($\mathbf{t}^*$) of each staff configuration.

Case number ($\mathbf{t}^*$)	Old case number	$\mathbf{ENR}_1$	$\mathbf{ENR}_2$	**euro**	**Time (hrs)**	$\mathbf{t}^*$ **(hrs)**
1	3	ENS	ENS	1,000	0.14	0.07
2	5	ENS	ENJ	850	0.18	0.08
3	4	ENJ	ENJ	700	0.18	0.09
4	1	ENS	-	500	0.14	0.14
5	2	ENJ	-	350	0.18	0.18

Table 11: Ordering staff configuration of x-ray technicians according to the equivalent operational patient-service time ($\mathbf{t}^*$) of each staff configuration.

Case number ($\mathbf{t}^*$)	Old case number	$\mathbf{XR}_1$	$\mathbf{XR}_2$	**euro**	**Time (hrs)**	$\mathbf{t}^*$ **(hrs)**
1	3	XRS	XRS	400	0.09	0.045
2	5	XRS	XRJ	350	0.14	0.055
3	4	XRJ	XRJ	300	0.14	0.07
4	1	XRS	-	200	0.09	0.09
5	2	XRJ	-	150	0.14	0.14

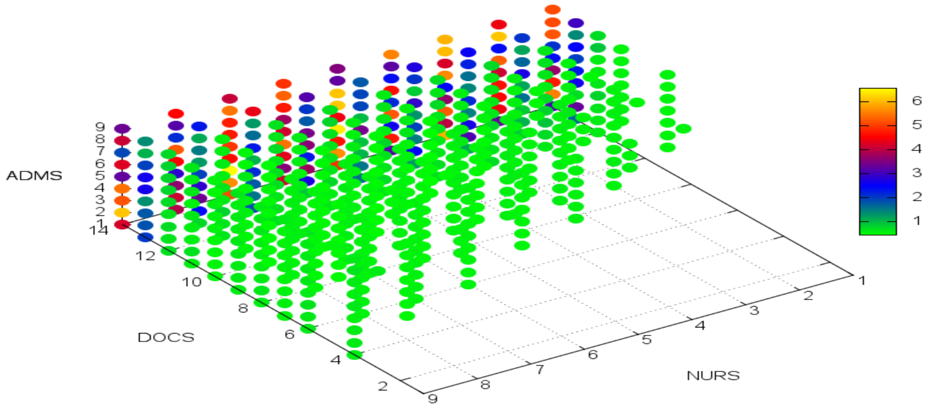

Figure 4: 3D scattered graph ordered by the equivalent operational patient-service time ($\mathbf{t}^*$) of a "single one" sanitary professional of each sanitary staff configuration 7 to 11. The green value region of interest was connected and almost "non" scattered.

Table 12: Incoming ED patients divided into four different workload scenarios, up to: 4, 9, 13, and 17 patients per hour for each scenario.

Workload scenario number	**Incoming patients (hourly)**
1	4
2	9
3	13
4	17

5.4 Evaluation Metrics

The set of metrics used in this work were: the length of stay (LoS) of the patients in the ED; the number of attended patients per day (Throughput); and a compound index, the product of the cost of a given sanitary staff configuration times patient length of stay (CLoS).

Furthermore, the computing time of each of the proposed optimisation method is measured in order to observe the gains in reducing computing time of the methodology proposed.

All simulations of the ED optimization cases analysed in this work were carried out in a Linux cluster of the CAOS Department of the UAB, which has 608 computing cores and 2.2TB of RAM, that is composed of: 9 nodes of a dual-4 core Intel Xeon E5430, 2.6GHz, 16GB RAM; 1 node of 2xdual-6 core Intel Xeon E5645, 2.4GHz, 24GB RAM; and 8 nodes of 4x16-cores AMD Opteron "Interlagos", 1.66GHz, 256 GB RAM, all in a switched 1GigE network.

5.5 Evaluation Method

The evaluation of the proposed methodology was aimed to confirm the correct operation of both the pipeline approach (PA), described in **??**. To this end, we have first performed the exhaustive search (ES) to use as baseline method. The second step of this evaluation consists on applying the coarse grained phase, using the PA. Finally, the fine grained phase is apply in the promising regions found in the previous step.

In order to evaluate quantitatively the proposal methodology two case studies were set. The first of them, namely case study A, was performed using the agent-based ED simulator version 1.1. This case study is further described in 5.6. The second case or case study B was performed using the agent-based ED simulator version 1.2 (the current version). This case study is further described in **??**.

In both case studies, only patients identified as triage level 4 and 5 are served at the stage of diagnosis-treatment phase, the three metrics, and the four different workloads stated above were tested, and the period simulated was 24 hrs., i.e., one day of functioning of the ED, in all the experiments. Test scenarios and evaluation results of both case studies are explained in detail in the following sections.

It is important to remind that the actions and interactions corresponding to the admission and triage processes have been totally implemented, but in the case of diagnostic and treatment phase, respecting to the priorities of the Sabadell Hospital ED currently only the level 1 was implemented. In such level 1 only patients identified with priority level 4 or 5 (less urgent, and non-urgent, respectively **??**) were taken care of. Nevertheless, all incoming patients were triaged. Once patients have been triaged, only patients identified as triage level 4 and 5 were served at the stage of diagnosis-treatment phase.

5.6 Case Study A

The agent-based ED simulator version 1.1, which is shown in 5, was used in this case study. In this version of the ED simulator the diagnostic and treatment phase is only addressed by doctors.

The simple patient flow in this ED simulator is defined as follows: patients arrive to the ED on

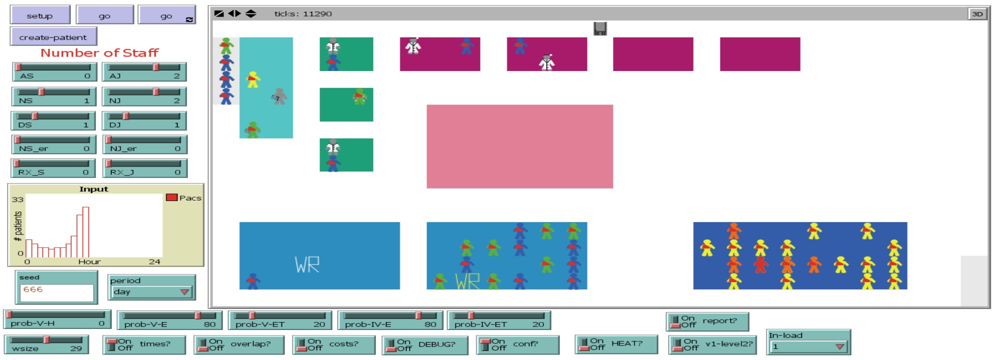

Figure 5: ED simulator v1.1. Admission personnel, triage nurses, and doctors were the sanitary staff considered.

their own, and waits to be attended in the admission area. Then, patients stay in the first Waiting Room (WR) WR1, until a triage nurse call them. After the triage process patients identified as triage level 4 and triage level 5 pass to a second WR2, and stay there until a free doctor calls them to begin the diagnosis-treatment phase, depending on the patient's symptoms, physical condition, and prescribed diagnosis tests. Finally, patients are discharged from the ED.

Therefore, in this case study the sanitary staff considered were: doctors, triage nurses, and admission personnel. Thus, only 2 to 6 were taken into account. As a result, 1,134 ($14D*9N*9A$) staff configurations were tested for each of the four workload scenarios of incoming patients stated in 12.

Finally, the three metrics above stated: LoS, Throughput, and CLoS were obtained by applying: the ES technique; the coarse grained phase, using the PA method; then, the fine grained phase was applied in the reduced feasible region to find the optimum.

5.7 LoS Index

The first objective set was to minimise patient length of stay (LoS) in the ED, with cost configuration constraint less or equal to 3,500 euro. This first index is expressed mathematically in 1:

$$\begin{aligned} &\text{minimise LoS} && f(D,N,A) \\ &\text{subject to} && D_{cost} + N_{cost} + A_{cost} \in Cost \leq 3,500\,\text{euro} \end{aligned} \tag{1}$$

It is worth noting that each of the plotted points for the following four workload scenarios were obtained running the ED simulator as many times as points are. Each plotted point corresponds to each of the 602 staff configurations (out of 1,134) that satisfy the cost restriction.

5.7.1 First Workload Scenario

The results of this scenario, up to 4 patients/hour, are shown from 6 to **??**. The ES result is shown in 6. The red triangle was the minimum.

The PA result is shown in 7, where four regions can be clearly seen and the red triangle was the minimum. The most important is the bottom region, in which the average minimum LoS was around 0.5 hours. There were 366 configurations (from a total of 602 in the feasible region) in this region, which is the one where the minimum was.

The 8 shows another way to visualise the connectivity characteristic of the reduced regions found by the proposed methodology. The axes of such graph are the equivalent operational patient-service time ($\mathbf{t}^*$) of a "single one" sanitary professional of each sanitary staff configuration (the first column of 7 to 9, where they were ordered by the PA **??**). In such figure, the points of interest were the green points, which lie in the region of interest, where the minimum was, which can be seen in black triangle. It can be seen that it was not necessary to search in the whole feasible region, but only in the green connected region.

Finally, after applied the PA method, the "reduced exhaustive search" was separately performed in each reduced region identified. The optimum found per each method: the ES and the PA methods are presented in 13, where the sanitary staff configuration (doctors, nurses, and admission personnel), their associated average minimum LoS, and cost configuration are shown. The three optima independently found were the same.

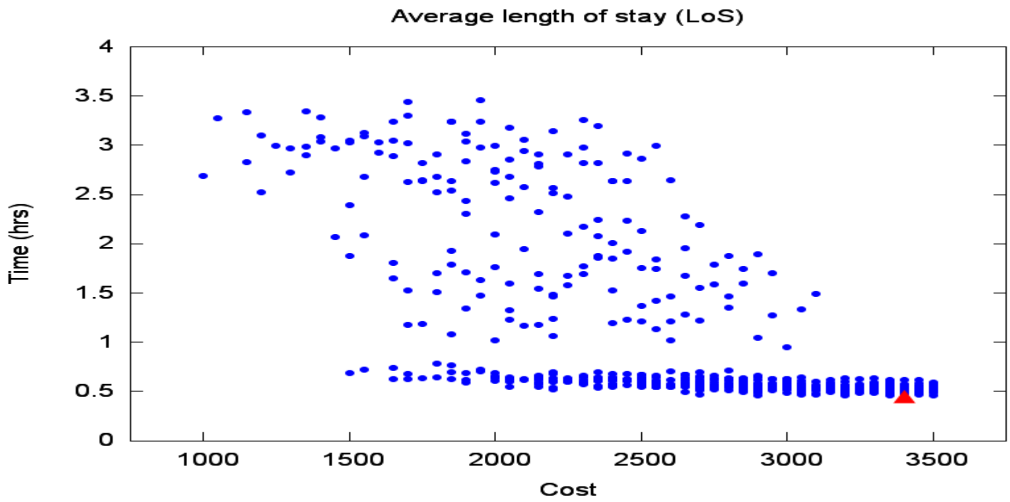

Figure 6: Average LoS obtained by the ES. The red triangle was the minimum.

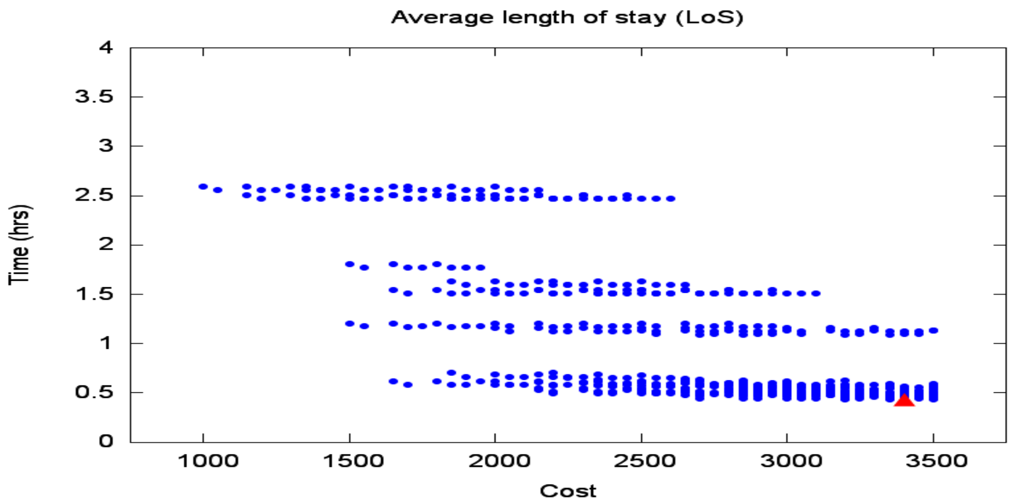

Figure 7: Average LoS obtained by the PA. The red triangle was the minimum.

Table 13: Optimum staff configurations that got the average minimum LoS for this workload scenario (up to 4 patients hourly), where S is Senior and J is Junior. This optimum sanitary staff configuration is shown in red triangle in 6 and in black triangle in 8.

Method	euro	LoS (hrs)	D	N	A	Run time (hrs) 4 Pthreads
ES	3,400	0.44	2S	2S	2S	0.89
PA	3,400	0.43	2S	2S	2S	0.53

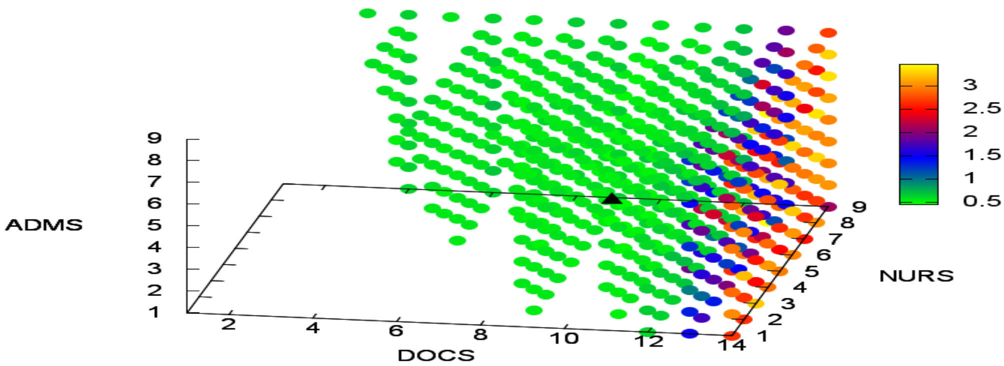

Figure 8: 3D scattered graph shows the average LoS index of the first workload scenario (4 patients/hour). The average LoS index in hours is represented in colour, and the minimum is the black triangle.

5.7.2 Second Workload Scenario

The results of this scenario, up to 9 patients/hour, are shown from 9 to **??**. The ES result is shown in 9, where the red triangle was the maximum.

The PA result is shown in 10, where many regions can be seen and the red triangle was the maximum. The most important is the top region, in which the average maximum Throughput was more than 150 attended patients. There were 180 configurations (from a total of 602 in the feasible region) in this region, which was the one where the maximum was.

Finally, after applied the PA method, the “reduced exhaustive search” was separately performed in each reduced region identified. The optimum found per each method: the ES and the PA methods are presented in 14, where the sanitary staff configuration (doctors, nurses, and admission personnel), their associated average maximum Throughput, and cost configuration are shown. The three optima independently found were the same.

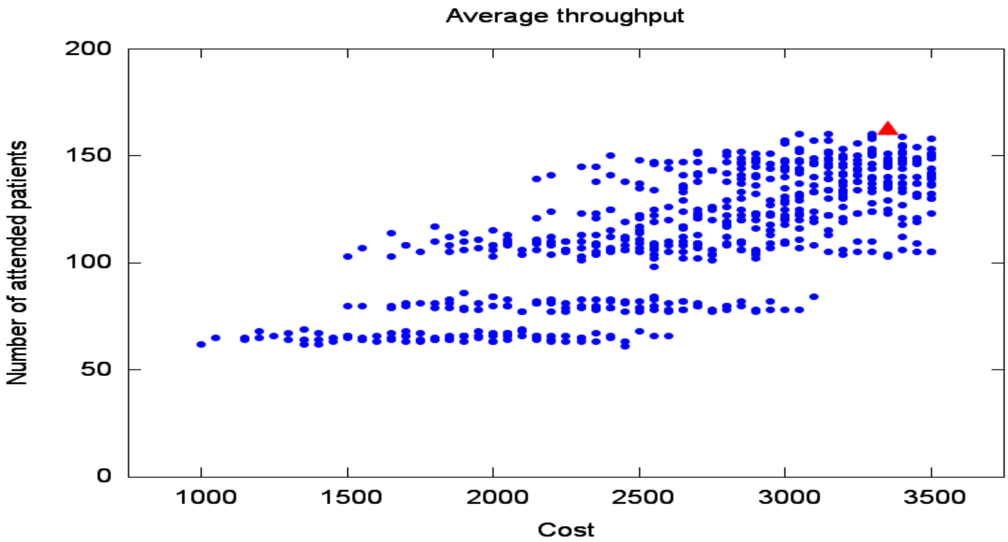

Figure 9: Average number of attended patients obtained by the ES method. The red triangle was the maximum.

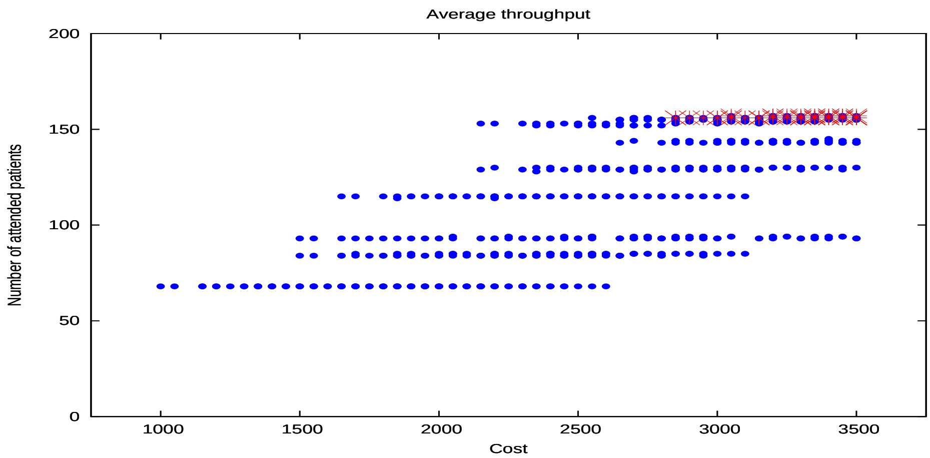

Figure 10: Average number of attended patients obtained by the PA. The red triangles were the maximum.

Table 14: Optimum staff configurations that got the average maximum Throughput for this workload scenario (up to 9 patients hourly), where S is Senior and J is Junior. These optimum sanitary staff configurations are shown in red triangle in 9.

Method	euro	#attended patients	D	N	A	Run time (hrs) 4 Pthreads
ES	3,350	163	1S,2J	2S	1S,1J	1.59
PA	3,350	163	1S,2J	2S	1S,1J	0.39

5.7.3 Third Workload Scenario

The results of this scenario, up to 13 patients/hour, are shown from 11 to 14. The ES result is shown in 11, where the red triangle was the maximum.

The PA result is shown in 12, many regions can be seen and the red triangle was the maximum. The most important is the top region, in which the average maximum Throughput was more than 200 attended patients. There were 21 configurations (from a total of 602 in the feasible region) in this region, which is the one where the maximum was.

Finally, after applied the PA method, the "reduced exhaustive search" was separately performed in each reduced region identified. The optimum found per each method: the ES and the PA methods are presented in 15, where the sanitary staff configuration (doctors, nurses, and admission personnel), and their associated average maximum Throughput, and cost configuration are shown. The three optima independently found were the same.

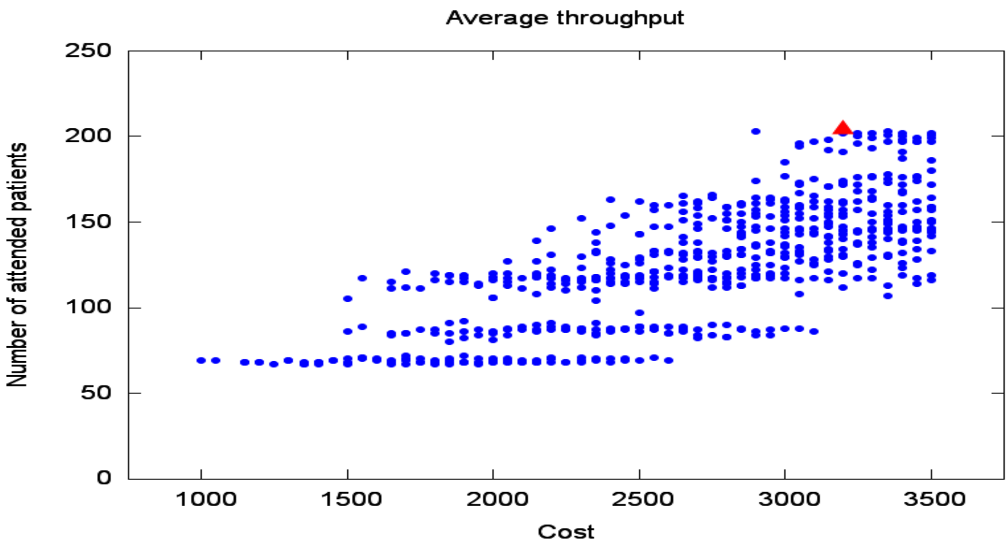

Figure 11: Average number of attended patients obtained by the ES method. The red triangle was the maximum.

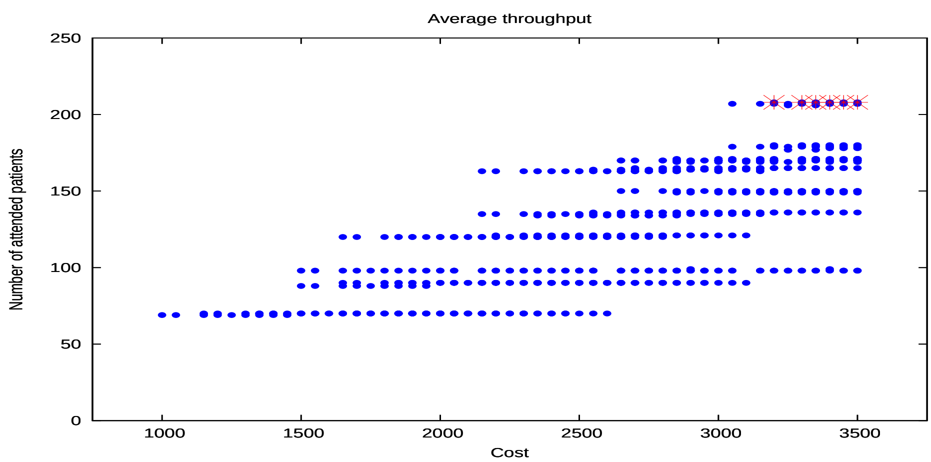

Figure 12: Average number of attended patients obtained by the PA. The red triangles were the maximum.

Table 15: Optimum staff configurations that got the average maximum Throughput for this workload scenario (up to 13 patients hourly), where S is Senior and J is Junior. This optimum sanitary staff configuration is shown in red triangle in 11.

Method	euro	#attended patients	D	N	A	Run time (hrs) 4 Pthreads
ES	3,200	205	4J	2S	1S	2.46
PA	3,200	205	4J	2S	1S	0.13

5.7.4 Fourth Workload Scenario

The results of this scenario, up to 17 patients/hour, are shown from 15 to 18. The ES result is shown in 15, where the red triangle was the maximum.

The PA result is shown in 16, many regions can be seen and the red triangle was the maximum. The most important is the top region, in which the average maximum Throughput was more than 200 attended patients. There were 21 configurations (from a total of 602 in the feasible region) in this region, which is the one where the maximum was.

Finally, after applied the PA method, the "reduced exhaustive search" was separately performed in each reduced region identified. The optimum found per each method: the ES and the PA methods are presented in 16, where the sanitary staff configuration (doctors, nurses, and admission personnel), their associated average maximum Throughput, and cost configuration are shown. The three optima independently found were the same.

Table 16: Optimum staff configurations that got the average maximum Throughput for this workload scenario (up to 17 patients hourly), where S is Senior and J is Junior. This optimum sanitary staff configuration is shown in red triangle in 15.

Method	euro	#attended patients	D	N	A	Run time (hrs) 4 Pthreads
ES	3,400	221	4J	3J	1S,1J	3.43
PA	3,400	221	4J	3J	1S,1J	0.10

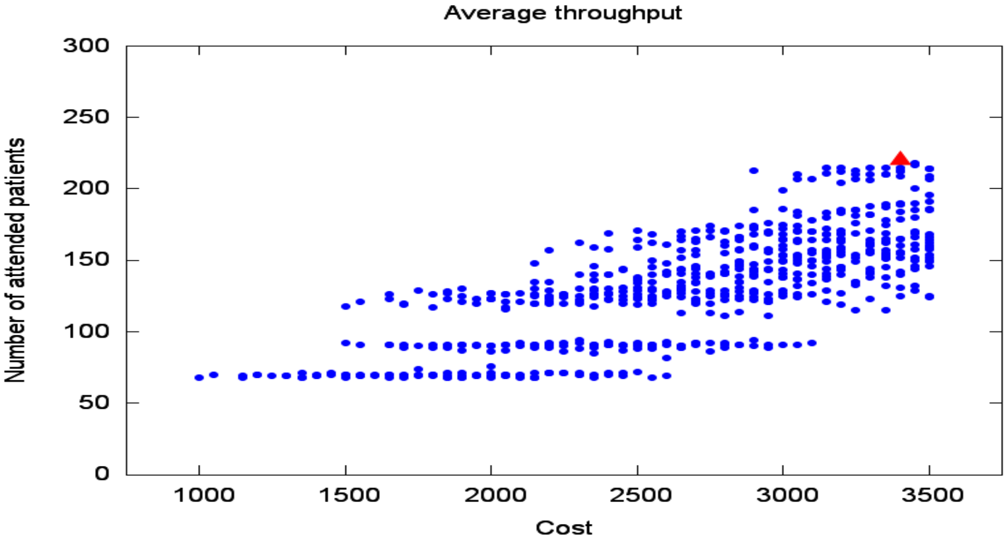

Figure 13: Average number of attended patients obtained by the ES method. The red triangle was the maximum.

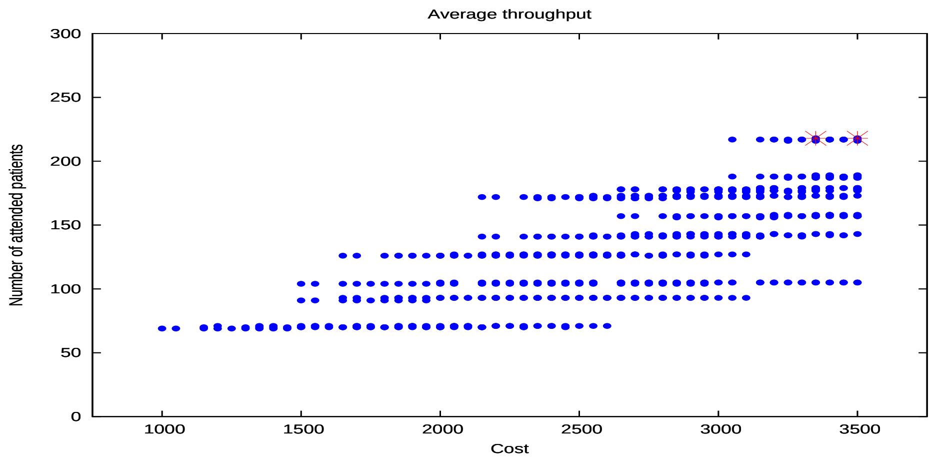

Figure 14: Average number of attended patients obtained by the PA. The red triangles were the maximum.

6 Discussion

The most relevant conclusions of this chapter are the following:

1. The two-phase optimisation via simulation of healthcare Emergency Departments proposed was applied to analyse the administrative strategies leading to optimum decisions about the physical and human resources of an ED. In particular, the impact on the economics and the productivity of Sabadell Hospital ED of different sanitary staff configuration (v.gr., doctors, triage nurses, admission personnel, emergency nurses, and x-ray technicians) were analysed.

2. The evaluation of the proposal included the *simulation models*; the *decision variables* and *workloads* used as inputs of the simulation models; as well as the *metrics* used to asses the benefits of the proposal. This metrics were defined in term of three indexes: patient length of stay (LoS) in the ED; number of attended patients per day (Throughput); and a compound index, the product of the cost of a given sanitary staff configuration times patient length of stay (CLoS).

3. From interviews with the managers at the EDs of Sabadell hospital (which provides healthcare services to an average of 160,000 patients/year), it was found that a basic sanitary of its ED staff is composed by: 9 possible combinations of admission personnel (junior/senior); 9 possible combinations of triage nurses (junior/senior); 5 possible combinations of emergency nurses (junior/senior); 5 possible combinations of x-ray technicians (junior/senior); and 14 possible combinations of doctors (junior/senior) in which a set of examined cases for each type of staff were analysed as a discrete combinatorial problem.

4. In order to analyse the performance of the ED, the real average four hundred incoming patients that daily arrive to the ED of Sabadell hospital was divided into four different workload scenarios, up to: 4, 9, 13, and 17 incoming patients hourly, i.e., up to 96, 216, 312, and 408, respectively for 24hrs.

5. All simulations of the ED optimization cases analysed in this work were carried out in a Linux cluster of the CAOS Department of the UAB, which has 608 computing cores and 2.2TB of RAM, that is composed of: 9 nodes of a dual-4 core Intel Xeon E5430, 2.6GHz, 16GB RAM; 1 node of 2xdual-6 core Intel Xeon E5645, 2.4GHz, 24GB RAM; and 8 nodes of 4x16-cores AMD Opteron “Interlagos”, 1.66GHz, 256 GB RAM, all in a switched 1GigE network.

6. The evaluation of the proposed methodology aimed to confirm the correct operation of the pipeline approach (PA) method, described in **??**. To this end, we have first performed

the exhaustive search (ES) to use as baseline method. The second step of this evaluation consisted on applying the coarse grained phase, using the PA. Finally, the fine grained phase was applied in the promising regions found in the previous step.

7. To evaluate the methodology proposed, first the case study A was performed using the agent-based ED simulator version 1.1. Then the case study B was performed using the agent-based ED simulator version 1.2. In both cases, the three metrics and the four different workloads stated above were tested, and the period simulated was 24 hrs., i.e., one day of functioning of the ED, in all the experiments.

8. After separately applying for cases A and B the pipeline approach, PA, the "reduced exhaustive search", the optimum found per each method for their associated average LoS, average Throughput, and average CLoS were the same.

9. Using the pipeline approach, PA, as the coarse grained phase of the proposed methodology and then the "reduced exhaustive search" in the promising regions previously found, our proposal obtained an improvement up to 95.6% in the computing time, compared with the exhaustive search used.

10. The optimum solution not always is the best option; it is important to take into account the sort of optimum when the solutions are going to be applied into real problems or decision support systems.

7 Conclusions

This paper presents a concrete example that uses a promising approach of an agent-based model to simulate Healthcare Emergency Departments (ED), whose complexity and dynamic nature make them difficult to characterize. The model uses Moore state machines based agents which act and communicate within a defined layout. In order to verify and validate the model an initial simulation has been made. An index defined as the minimum patient length of stay (LoS) was set to evaluate the operation of the agent-based Emergency Department simulator. The search of the optimum LoS was done through an exhaustive search technique, which implies a large searching time. The obtained results are encouraging, since they not only showed that as expected, the larger number and experienced ED staff, the less average patient LoS is estimated, but also showed interesting results when its standard deviation is analyzed. Simulation allows to understand and analyze better the problem. However, even with the pretty small problem size studied the number of combinations are large, as well as the execution time. Moreover, the computational resources that this problem will demand in order to perform statistical sensitivity analysis are huge. Therefore, a better optimization technique or approach, rather than exhaustive search technique, must be used. This approach is using a computationally simplified model of the ED as MC and Pipeline schemes in order to identify the region where the optimum is, and do a reduced exhaustive search, in this limited region. The results using such approaches are not only promising, but also computationally not as intense as the computing using exhaustive search technique.

Acknowledgments

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