An Analytical Model to Evaluate the Response Capacity of Emergency Departments in Extreme Situations

Work-in-Progress Paper

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***Abstract*—One of the most important current problems in the healthcare system is the saturation of Emergency Departments, due to the increasing demand of the service. Healthcare staff often has no margin to absorb the demand in case of an unexpected increase of patients entering the service caused by an emergency. We aim to evaluate the response capacity of an Emergency Department, specifically of doctors, nurses and specialist technicians that make up a specific sanitary staff configuration, facing an unexpected emergency. Such situations cannot be tested in the real system and simulation is the only way to obtain data about them. We present an analytical model to obtain information from data obtained through the simulation of a Hospital Emergency Department. The model defines how to calculate the theoretical throughput of a particular sanitary staff configuration, that is, the number of patients it can attend per unit time given its composition. This index is a reference in order to measure the emergency response capacity of the system and also other indicators concerning to performance. The data for the analysis will be generated by the simulation of any possible scenario of the real system, taking into account all valid sanitary staff configurations and different number of patients entering into the emergency service. The designed model offers the availability of relevant knowledge to the managers of the service to make decisions concerning the composition of the sanitary staff configuration in anticipation of extraordinary situations.**

Keywords—Agent-Based Modeling and Simulation (ABMS); Decision Support Systems (DSS); Emergency Response Capacity; Emergency Department (ED); Knowledge Discovery.

I. INTRODUCTION

Currently, given the growing demand of emergency medical care, the management of Emergency Departments (ED) is increasingly important. Particularly, how to manage the increasing number of patients entering into the service is one of the most important problems in the ED worldwide, because it requires a substantial amount of human and material resources, which unfortunately are often too limited, as well as a high degree of coordination between them [1][2]. A major consequence of the increase of patients entering the service is its saturation [3]. This results in an increase in the length of stay of patients in the service, which produces a general discontent among them, abandoning patients without receiving care, limited access to emergency care and an increasing patient mortality [4].

A sudden or unexpected increase in the entrance of patients is an extraordinary, but possible situation, which most likely cause the collapse of the service. The response capacity of the system in anticipation of such situations is the leeway of the sanitary staff configuration to absorb an extra demand of the service, and it will depend on its composition. Also, the waiting time of patients for medical attention and the total time spent in the service, which are indicators of the quality of service from users' point of view, will heavily depend on the configuration composition.

Even though computerized systems in hospitals provide more and more real data, there are no real data available to analyze concerning this kind of situations, which cannot be tested in the real system, but this limitation can be overcome through computer simulation.

There are many examples of computer simulation models that support decision-making processes in the health sector [5][6][7][8]. Specifically, simulation has been widely used to understand causes of ED overcrowding and to test interventions to alleviate its effects, and many contributions show how simulation can be used as a tool to address this problem. An extensive review of this related work is done in [9].

Our contribution in this context consists on using simulation as a sensor of the real system, being our main source of data, an ED simulator, based on an Agent-Based Modeling (ABM) design of the system [10]. The simulator has been developed, verified and validated by the "High Performance Computing for Efficient Applications and Simulation" Research Group (HPC4EAS) of the Universitat Autònoma de Barcelona (UAB) in collaboration with the Hospital de Sabadell (Parc Taulí, Barcelona). The input parameters that characterize each different scenario in the simulation of the real system are the healthcare staff configuration, the number of incoming patients, the derivation percentage of patients and the period of time simulated. In addition, each simulation provides data of the length of stay of all patients in all locations in the ED and the

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number of patients per hour and location [11][12]. The number and variety of simulated agents and the different possible values for the input parameters of the simulator, give a great number of different possible scenarios to execute. Each execution will generate the corresponding data based on the designed model.

The paper is organized as follows: Section II presents the research objectives and methodology; Section III describes the Emergency Department process; Section IV presents the analytical model proposed. Finally, Section V closes the paper with discussion and future work.

II. Research Objectives and Methodology

The general purpose of our research is to gain knowledge about the variables that may influence in the performance and the quality of service of an emergency department from the data generated via simulation of the real system for any possible situation.

Specifically, the goal of this work is to develop an analytical model to obtain information about the emergency response capacity of the system. This will provide staff demand prediction models in the service, especially for unusual situations, as a reference to make decisions and to anticipate solutions in exceptional cases.

The simulator will be the main source of data. These data are the raw material for the analysis. When the user assigns them some special meaning, they become information. We refer to as knowledge when a model is found or designed, in order to interpret this information, and the model represents an added value [13]. Therefore, the analysis of the data generated by the simulator can give us prediction and behavior models for an emergency department for any possible situation. In particular, our specific objective is to determine the features associated to a sanitary staff configuration to ensure an acceptable response capacity in anticipation of a possible emergency situation.

With this objective in mind, an analytical model has been designed for the processing and analysis of the raw data obtained directly from the simulator.

III. Description of the Simulation Model

A. Emergency Department Process

The operation of the ED is based on a process consisting of different steps or phases on which each patient is passing from its entry into the service until it is discharged, referred to another service or admitted to the hospital.

The ED is divided into different areas, which correspond with the different process phases:

- *Admissions Area*: Administrative staff carries out the registration of the patient's arrival and the reasons for his visit to the emergency service.
- *Triage Area*: Professional sanitary staff identifies the priority level with which the patient should be treated.
- *Diagnosis-Treatment Zone*: Sanitary staff (doctors, nurses and specialist technicians) tries to identify the causes of the patient's health problem, and to the extent possible, try to solve it. This area is in turn divided into different areas or zones (medical room, nursing room, care boxes and X-ray laboratories).
- *Waiting Rooms*: Distributed in different zones of the ED, where patients wait to be treated at the different stages of the process.

B. Functionality of the Simulator

The simulator includes the following agents: patients, admissions staff, triage nurses, assistant nurses, doctors and radiology technicians. In the case of agents representing sanitary staff (all except patients), we consider two levels of experience (Junior/Senior) and all of them can work in parallel on each phase.

The actions and interactions between the involved agents at each process step result in changes of state of the agents, which ultimately result in the global operation of the system.

From the moment when the patient enters the service, the simulation runs according to the patient flow shown in Figure 1.

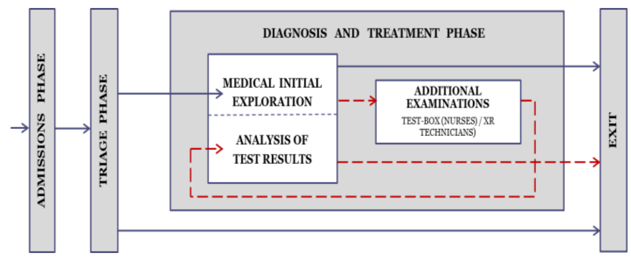

Figure 1. Patient flow in the emergency department.

The admission and triage phases are common to all patients entering the service, and there is a percentage, although low, of patients being referred to other services after triage stage.

In the diagnostic and treatment phase, all patients generated by the system go through an initial medical exploration phase. Some of them are discharged and leave the ED (in blue in Figure 1). The rest remain in the ED and they go through a phase of complementary examinations carried out by technical staff and/or clinical nurses. After this they return again with the doctor who analyzes the test results and, finally, they are discharged from the service (in red and dashed line in Figure 1).

For a given number of patients in the service, the simulation runs for all possible sanitary staff configurations. Each scenario is identified by a sanitary staff configuration and a specific input of patients into the service, and the output of the simulation brings data concerning the number of attended patients, attention time and waiting time for each patient in all phases in their way through the service.

IV. Analytical Model

In order to transform this raw data directly generated by the simulation and to visualize the potential information which they contain, we have defined a set of indexes that characterize numerically each scenario and, in particular, each configuration. These defined indexes facilitate the treatment and analysis of latent information in data.

A. *Definition of indexes*

As an indicator of the quality of service from the point of view of the user, we define an index called *Patient attention Time (PaT)* as the total time a patient is receiving attention throughout all stages in the service for a given configuration. Another indicator of quality is the *Length of Stay (LoS)* defined as the total length of stay of a patient in the service. And finally the *Length of Waiting (LoW)* is the total waiting time of a patient along the service. Note that,

$$\text{LoS} - \text{PaT} = \text{LoW} \text{ and always } \text{PaT} \leq \text{LoS}. \quad (1)$$

Moreover, the *Equivalent Patient attention Time* for the stage *i* ($EpaT_i$) is defined as the attention time of a patient taking into account the possibility of working in parallel for the agents in that stage, and (2) shows how is calculated:

$$EPaT_i = \frac{1}{\sum_{j=1}^{staff} \frac{1}{PaT_{staff_j}}} \quad (2)$$

where PaTstaff $_j$ represents the value of the attention time corresponding to each type of sanitary staff, depending also on their level of experience. This values result from the simulator's calibration with the historical real data provided by the hospital.

The slowest phase of the configuration will fix the speed at which patients can be attended in the service and also is the one which can saturate the system. It is, therefore, the equivalent attention time of the slowest phase, which will determine the number of patients that a given configuration can treat per unit of time, given its composition. We call this index *Theoretical Throughput (T_ThP),* which is an indicator patients' attention capacity of the configuration. Expression (3) gives its calculation:

$$T\_ThP = \frac{1}{Max\ EPaT_i} \quad (3)$$

It is also defined the *Real Throughput (R_THP)* index as the real number of patients treated per unit time. This is an index which values are direct output data from simulation. Then, the ratio between real and theoretical throughput is defined as an indicator of *Performance (PeR)* of a given configuration for a specific scenario:

$$PeR = \frac{R\_ThP}{T\_ThP} \quad (4)$$

B. *Theoretical throughput for the diagnosis and treatment phase.*

Unlike other stages of the process of a patient along his pass through the emergency department, this is the most complex stage due to its nonlinearity. The return of patients for the doctor's final diagnosis after completing complementary examinations requested by the doctor after his first contact with the patient (initial exploration phase), must be taken into account.

We have defined the *Theoretical Throughput (T_ThP)* as an indicator of the attention capacity of each phase, that is, as the number of patients that, for its composition, this phase could treat.

In this phase, the attention time of each type of doctor depending on their experience (Junior or Senior) and depending on the type of care they are doing, either in the first step of initial exploration, or in the second, consisting of the analyzing of the results of a requested supplementary examination, are known and denoted by:

- $IPaT_{S/J}$: Attention time of a senior/junior doctor in the Initial Exploration phase (I).
- $ARPaT_{S/J:}$ Attention time of a senior/junior doctor in the Analysis of Results phase (AR).

Given these times, their inverse will give us the number of patients that each doctor can treat per unit time considered.

Moreover, we represent with *D (Doctors)* the total number of doctors in the considered combination. Then:

- DSI = Number of senior doctors attending patients in the Initial Exploration phase.
- DSA = Number of senior doctors attending patients in the Analysis of Results phase.
- DJI = Number of junior doctors attending patients in the Initial Exploration phase.
- DJA = Number of junior doctors attending patients in the Analysis of Results phase.

We consider a sufficient rate of patients entering into the service to ensure that the system is running continuously and we assume the system is in a steady state. We also contemplate that doctors prioritize the attention of patients who have already gone through the first exploration phase, and therefore, these patients will be treated at the time the doctor has availability. This prevents endless queues at the return of patients from their requested complementary examination.

Given all these preliminary considerations, in the specific case with only senior doctors, and a percentage p_t of patients who require additional tests, we obtain the following relation of continuity:

$$\frac{DSI}{IPaT_S} \times \frac{p_t}{100} = \frac{DSA}{ARPaT_S} \quad (7)$$

being $DSI + DSA = D$, the total of doctors in the configuration.

Then, the *Theoretical Throughput* of the doctor's combination is calculated in (8):

$$T\_ThP_{diag\&trat} = \frac{DSI}{IPaT_S} \times \frac{100 - p_t}{100} + \frac{DSA}{ARPaT_S} = \frac{DSI}{IPaT_S} \quad (8)$$

From (7) and considering $DSI + DSA = D$ we can obtain DSI, and then obtain the value for the Theoretical throughput of the diagnosis and treatment phase (diag&trat) in (8), in the considered case.

It rests to make a generalization of the model for any possible combination of doctors (senior or junior).

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C. Emergency Response Capacity of the system

We define the Emergency Response Capacity of the system (ERC) as the capacity of a given configuration to provide extraordinary service to patients in an exceptional situation related with an unexpected increase in the number of patients requiring urgent attention.

The desired leeway of the sanitary staff configuration to absorb an extra demand of the service, can be fix in terms of the percentage of patients from its theoretical capacity, that the current configuration should be able to absorb, in expectation of possible but unexpected situations related to a surge in patients entering the service. Considering this, the *Emergency Response Capacity (ERC)* for a given configuration, can be defined as:

$$ERC = T\_ThP \times \frac{p_e}{100} \quad (9)$$

where T_ThP is the theoretical capacity (number of patients per unit time) of a specific sanitary staff configuration, or a specific phase, and it has been defined in (3).

This percentage also establishes a maximum throughput for the considered configuration, or specifically, for each stage, in normal situation, that is:

$$ThP_{máx} = T\_ThP \times \frac{100-p_e}{100} \quad (10)$$

The ultimate goal is to anticipate the best mix between each type of sanitary staff (senior/junior), and the total number of sanitary people to be able to ensure the established emergency response capacity.

V. CONCLUSION AND FUTURE WORK

The initial contribution of the research is the idea of using the simulator of the ED as source of intensive data (sensor of the real system), as it brings the possibility of obtaining data from simulation of any kind of situations, including those which cannot be tested in the real system.

Other contribution to knowledge of the presented work, is the definition of a model to analyze these intensive data to obtain the potential information contained in data, related with the influence of the staff configuration on the efficiency, the performance and the exceptional response capacity of the system.

As immediate future work, in order to check that the proposed model works well, we will try to extract information from a set of data already available, which finally would allow us to obtain relevant knowledge through the values of the defined indexes for all the simulated scenarios.

To do this we will begin working with the data generated by the execution of the simulation of 93780 different scenarios with a reduced version of the simulator [14]: 23445 different staff configurations and four different inputs for the number of patients, one corresponding to a regular situation, and the rest simulating other extraordinary situations. The generated data processing will consist in obtaining the values of the defined indexes in the model, for all the executed scenarios.

The information from the indexes will allow us to see similarities between configurations with lower values of LoS, which will give us a first approach to the desirable features for a configuration regarding the quality of service from the point of view of the patient, user of the service. To perform this study we plan to use data mining, in particular k-means clustering method, which should allow us to visualize common characteristics between configurations in the same cluster.

Moreover, the analysis of the emergency response capacity and performance of the system, should lead us to identify the characteristics of the most suitable configurations facing an increase in the number of input patients, and therefore, this is desirable knowledge from the point of view of the service manager. It could also be interesting, for further work, the selection of new useful indexes and generation of their models.

Finally, we aim to translate and extrapolate the model to a general model, as the basis for the processing and analysis of data generated by the simulator in its extended version [15].

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