

SCHEDULING MODEL FOR NON-CRITICAL PATIENTS ADMISSION INTO A HOSPITAL EMERGENCY DEPARTMENT

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ABSTRACT

The saturation of the Emergency Department services is mostly due to admission of non-urgent or minor-urgency patients who represent a high percentage of admitted patients in the service. We propose a model for scheduling the entry of these non-critical patients into the Emergency Department which may be helpful for the management of the service dealing with the current growing demand for emergency medical care. We hypothesize that a relocation of these non-critical patients in the expected input pattern, initially provided by actual historical data from the hospital, can lead to an improvement in waiting times for all patients, and therefore, to an improvement in the quality of service from the point of view of the service users, as it could avoid long waiting times in the service. Simulation is used to show and evaluate the effect of applying the proposed scheduling model.

1 INTRODUCTION

Currently there is a growing demand for emergency medical care and thus the management of Hospital Emergency Departments (EDs) is increasingly important. Particularly, how to manage the increasing number of patients entering into the service is one of the most important problems in EDs 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 (Kadri et al. 2014). A major consequence of the increase in patients entering the service is its saturation (Boyle et al. 2012). This results in an increase in the total time a patient spends in the service, from their entry to their discharge, called Length of Stay of patients in the service (LoS), which is the most widely used and accepted parameter in the literature as an indicator of the quality of service. This can produce a general discontent among patients for reasons such as being abandoned without receiving care, limited access to emergency care and an increasing patient mortality.

Moreover, the ED service is one of the most complex areas of the hospitals due to its dynamism and variability over time. The operation of the system is the result of the interaction between the different elements of which it is composed, and all this makes it a complex real system.

Modeling and simulation of complex real systems, such as an ED, is one of the most powerful tools available for their description. Simulation provides a better understanding of their operation and of the activity of their elements, and it can help decision-making to establish strategies for an optimal system operation (Mancilla 1999, Pavón et al. 2006).

As a result of an intensive previous research, we have an ED simulator available, based on an Agent-Based Modeling (ABM) design of the system, which has been developed, verified and validated within our research group in collaboration with the ED Staff Team of the Hospital de Sabadell (one of the most important hospitals in Spain, which attends 160,000 patients per year in the ED). The model describes the ED's behavior from the actions and interactions between agents, as well as between them and their physical environment and it has been implemented with NetLogo, an agent-based simulation environment well-suited for modeling complex systems (Taboada et al. 2011, Liu et al. 2014).

We propose a model for scheduling the entry of non-critical patients into the ED and the simulator is used as an evaluation tool of the results of the application of the proposed model. In fact, simulation is the only way to show the improvement achieved by the model application. Based on historical real data from the Hospital de Sabadell, these patients represent a high percentage of the patients admitted into the ED, and it is observable that saturation in the ED service is mostly due to admission of these non-critical patients, those who do not require urgent attention or require deferred valuation (Bruballa et al. 2015). The proposed model consists of the relocation of these patients from their expected arrival time in the input pattern initially predicted by the historical data of the referred hospital, so that this relocation will bring about an improvement in the waiting times of all patients, and therefore an improvement in the quality of the provided service from the point of view of the patient who is receiving it.

As previous work in our current research, we have developed an analytical model which we introduced in Bruballa (2015) to calculate the theoretical throughput of a particular healthcare staff configuration in an ED, which is the number of patients it can attend per unit time given its composition. The model is based on the definition a set of equations to calculate its attention capacity, given an specific healthcare staff configuration. This model has already been validated, and it's a reference for the scheduling model presented here.

The paper is organized as follows: Section 2 highlights some related works; Section 3 gives a brief description of the operation and main features of the ED, as well as the simulator capabilities; Section 4 presents the research objectives; Section 5 contains the details of the scheduling model for non-critical patients' admission and the related experimental results are presented in Section 6. Finally, Section 7 closes the paper with a brief conclusion.

2 RELATED WORKS

Many other studies in the related literature aim to reduce the LoS, and therefore, the total time the patient is waiting to be attended, or length of waiting for patients (LoW), and some of the solutions that have been found and have been implemented are called Fast Tracks (Rodi, Graw, and Orsini 2006), or other measures known as See and Treat (Davies 2007). Other works try to analyze the factors that influence patients' long periods of stay of in the ED and its saturation (Yoon, Steiner, and Reinhardt 2003; Hoot and Aronsky 2008). Others show that saturation and long waits increase the proportion of patients who leave the service without being seen by a doctor (LWBS) (Stock et al. 1994). Another study in our same research group consisted of trying to find the optimal healthcare staff configuration to minimize the LoS of the patients in the service, taking into account a constraint related to the cost of the configurations and the amount of available resources (Cabrera et al. 2012). Finally, we highlight those references also using simulation to test the effectiveness of the proposed measures for improvement in the LoS of patients in

the ED (Samaha, Armel, and Starks 2003; Wang et al. 2001; Tan, Lau, and Lee, 2013; Medeiros, Swenson, and DeFlicht 2008).

Our current work tries to go a step further in order to obtain a different way to reduce the LoS of patients in the ED, so that the improvement of the quality of the service is achieved not by modifying the staff configuration nor the available resources, but by changing the way non-critical patients arrive into the service. As in the previously related papers, simulation provides us the way to measure the quality improvement in the service by the proposed model application.

3 EMERGENCY DEPARTMENT MODEL AND SIMULATOR

3.1 A brief Description of the Emergency Department Operation

The operation of the ED is based on a process consisting of different steps or phases which each patient passes through from their entry into the service until they are discharged, referred to another service or admitted to the hospital, as shown in Figure 1.



Figure 1: Operation of the Emergency Department.

In the triage phase, patients are classified according to their acuity level and they are assigned a priority. The scale of priority and urgency to be applied in Spanish hospitals (Spanish Triage System) is based on the Andorran Triage Model (MAT) (Soler et al. 2010) (Table 1).

Table 1: Classification of patients according to their level of urgency (Spanish Triage System).

ACUITY LEVEL	TYPE OF ATTENTION	DESCRIPTION	Hospital de Sabadell Historical Data
Level 1	Revival	Extreme health condition life-threatening. It requires IMMEDIATE ATTENTION.	0.5%
Level 2	Emergency	Health condition life-threatening. It requires IMMEDIATE ATTENTION. BUT NOT PRIORITY.	5.5%
Level 3	Urgency	Acute condition but not life threatening. Requires NOT IMMEDIATE EVALUATION.	30%
Level 4	Minor Urgency	Acute condition, not life threatening. EVALUATION CAN BE DEFERRED.	51%
Level 5	Not Urgent	Symptomatic condition, not life threatening. DOESN'T REQUIRE URGENT ATTENTION. OUTPATIENT.	13%

The distribution of patients by acuity level from historical real data of *Hospital de Sabadell* is shown in the last column of Table 1. A statistical analysis of this data corroborates that the majority of patients attending the service are not critical patients and, therefore, they do not require immediate assessment or can be outpatients.

If these non-critical patients had the possibility of getting information about when it is more advisable to go to the service, depending on the waiting time estimated for them, they would probably do it when the likelihood of waits was lower. These are the patients who could benefit from a scheduling model for admission in the ED.

3.2 Patient Flow in the Simulator

The simulator includes the following agents: patients, admissions staff, triage nurses, assistant nurses, doctors and radiology technicians. 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 the patient enters the service, the simulation runs according to the patient flow shown in Figure 2. The admissions and triage phases are common to all patients entering the service and they share the same healthcare staff. After triage, doctors and assistant nurses are different for patients with acuity level 1, 2 and 3, who are treated separately from those with acuity level 4 and 5 for the diagnostic and treatment phase. Also there is a percentage, although low, of patients being referred to other services after the triage stage and others who leave the service without being seen by a doctor.

For our work, we are interested in tracking patients 4 and 5, those who are non-critical patients, and can be relocated in time for their arrival to service. So we will consider all patients for admissions and triage phases, but only patients 4 and 5 for the diagnosis and treatment stage. In this stage, all patients generated by the system go through an initial medical exploration phase. A percentage of them are directly discharged and leave the ED after this phase (showed by a continuous line in Figure 2). The rest remain in the ED and they go through a phase of complementary examinations and/or treatment carried out by technical staff and/or nurses. After this, they return to see the doctor, who analyzes the test and/or treatment. Finally, they are discharged from the service (showed by a dashed line in Figure 2).

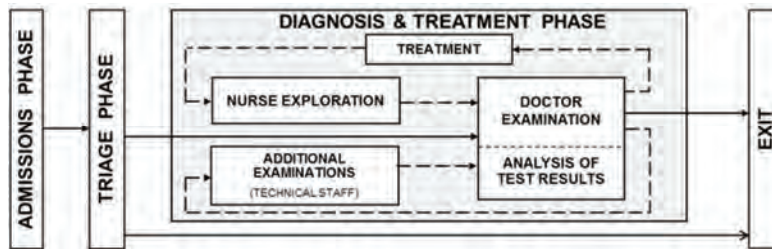


Figure 2: Patient flow in the Emergency Department.

Each scenario of simulation is identified by a healthcare staff configuration and a specific input of patients into the service (number and type of incoming patients each hour). The simulator includes sensors to obtain fully temporalized information about the output for each execution, which produces data concerning the number of attended patients, patient attention time (PaT) and waiting time (LoW) for each patient in all phases in their way through the service.

4 RESEARCH OBJECTIVES

This research aims to improve the quality of service provided in a ED, trying to reduce LoS of patients, through a model for scheduling the entry of non-critical patients into the service. The implementation of this admissions scheduling model should improve quality of care, optimize the quality perception about the attention paid to population, and contribute to the sustainability of the current system, ensuring better use of available resources. Therefore, our proposal aims to improve the ED service, which is the main entrance of patients in the healthcare system, in relation to access, quality and user satisfaction.

The final aim of the research is to dynamically adapt the current pattern of patients entering the service to its attention capacity, so that the flow of patients in the service shall be in accordance with the response capacity of the system, according to the healthcare staff resources available in the ED at any time.

5 SCHEDULING MODEL FOR NON-CRITICAL PATIENTS ADMISSION

The scheduling model for the entry of non-critical patients into the ED is built based on the information extracted from the historical data of the hospital and the system characterization in terms of its response capacity to patients' attention, called system theoretical throughput (ThP).

A first step on the way to the definition of this model consists of developing an analytical model based on the definition of a set of indicators of the quality of service, and a set of equations which allows us to determine the ThP value according to a particular healthcare staff configuration, which we define as the number of patients it can deal with per unit time given the available personnel resources and considering the patient flow presented in Figure 2. The corresponding value for the ThP is an indicator of the system capacity to absorb the demand for the service and a constraint in our model (Bruballa 2015).

The diagram in Figure 3 gives an overview of the full cycle needed to dynamically obtain an appointment scheduling for the admission of non-critical patients into the ED, according to the current hourly demand.

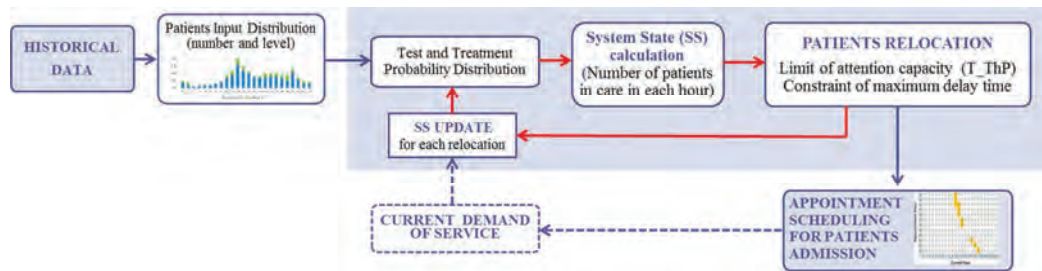


Figure 3: Scheduling model for non-critical patients admission into the ED.

The final goal of the model is to have an action plan as a tool for recommendation to potential non-critical patients regarding their admission into the system. The model is based on the patient scheduling algorithm. In addition to taking into account the attention capacity of healthcare staff as a restriction, and a constraint concerning the maximum delay time for patients relocation, the algorithm is based on the detailed knowledge of the system state hour by hour dynamically, which in turn is generated from the information extracted from the corresponding historical data and the changes made to it according to the real demand of the service, regarding the entry of patients and the type of care received.

5.1 Distribution of Patients Being in Care: System State

System State is defined through determining the number of patients in the system in each hour, only focusing on the Patient Attention Time (PaT), which includes the total time someone from the healthcare staff (doctor, nurse or specialist technician) is attending the patient, the required time for some treatment and/or time for other kinds of additional explorations. So the information in the state of the system doesn't consider the possible waiting time for patients (LoW). This information gives us a more realistic representation of what happens in the system hour by hour.

From actual historical data from the hospital we know the distribution of patients arriving in the ED, which gives us an initial estimation of the number of non-critical patients arriving each hour (*Historical Entry Patients* in Table 3). Patients who need no complementary examination (test) or treatment are discharged after the initial exploration by the doctor (IE) and need less than one hour to be attended (*Direct Patients* in Table 3). On the other hand, there is an average of four hours for patients who receive some treatment, and two hours for those who need any additional test are needed for their complete attention. For each hour, we obtain the number of these patients, respectively *Test and Treatment Patients* in Table 3, through the test and treatment probability distributions, which are also inferred from hospital

historical data. PaT values have been estimated from the calibration of the simulator according to actual historical data from Hospital de Sabadell. Moreover, it is important to point out that the simulator considers a random exponential distribution to model the real behavior of PaT, depending on patients acuity level and age (Liu et al. 2017). A statistical analysis of simulation data results in the mean PaT value for patients, depending on whether or not they require some treatment or test (Table 2).

Table 2: PaT average values (Hospital de Sabadell).

Type of attention	IE + Treatment	IE +Test	Only IE
Mean PaT	4 hours	2 hours	< 1 hour

According to PaT values in Table 2, the propagation of these patients during the following hours after their arrival hour in the service must be considered, because they will be receiving attention during these hours. Table 3 shows *test and treatment propagated patients* for an input arrival of patients specified in the *Historical Entry Patients* row, corresponding to input data for a specific day (Monday) according to the historical data of the hospital. Propagation time for each patient regards the average PaT in Table 2, and for each hour i $Propagated\ Patients_i = Test\ Patients_{i-1} + Treat\ Patients_{i-1} + Treat\ Patients_{i-2} + Treat\ Patients_{i-3}$.

Table 3: System State calculation.

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Historical Entry Patients	4	3	2	2	1	2	2	4	7	11	17	15	13	10	9	13	13	11	11	10	11	8	6	5
Direct Patients	3	2	2	2	1	2	2	3	5	8	12	10	9	7	6	9	8	8	7	8	6	5	4	
Test Patients	1	1	0	0	0	0	0	1	1	2	4	4	3	2	2	3	3	2	2	2	2	1	1	
Treatment Patients	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	
T&T Propagated Patients	1	1	1	0	0	0	0	0	1	2	4	7	7	6	5	5	6	6	5	5	5	4	2	
System State (Patients in Care)	5	4	3	2	1	2	2	4	8	13	21	22	20	16	14	18	19	17	16	15	16	13	10	7

Finally, the summation of *Entry and Propagated Patients* leads to the *System State* row, which is the hourly distribution of patients in care. Then the number of patients inside the service in the hour i is the corresponding value for $System\ State_i = Entry\ Patients_i + Propagated\ Patients_i$.

A graphical representation of the calculated System State in Table 3 is shown in Figure 4.



Figure 4: System State bar chart for a Monday input according to *Hospital de Sabadell* historical data. Then we consider that:

Each bar represents all patients in the service in the corresponding hour, but separated by patients arriving during this hour and discharged after a first visit with the doctor (PaT of less than an hour); and patients arriving during this hour or those who arrived during previous hours but who require some test or treatment, so they are propagated in time according to the corresponding PaT for each case (Table 2). The arrival hour for this latter type of patient in the service is showed in all bars, first in the corresponding bar to their arrival and again in the following bars, which correspond to all the hours while they are being treated by a doctor or receiving some test or treatment. We use the notation *hour:patients* in the bar chart in Figure 4 to show this information. It also helps to follow these patients in the bar chart.

The horizontal dashed lines represent three different values for the attention capacity of the system (ThP), which indicates the ideal situation with respect to patient attention, so that if patients per hour do not surpass this value, nobody would wait for attention. ThP value also indicates whether or not it is possible to improve the situation, relocating patients in such way that the number of patients per hour becomes as homogeneous as possible and does not exceed the limit value, which is the ThP value.

- If the limit value is above the maximum attention requirements, the system is oversized and there should be no saturation. No changes are needed.
- If the limit value is below minimum service requirements, there's no option for patients' relocation below ThP and the system cannot escape saturation without modifying resource availability. Even so, possibly there is the option to improve the situation slightly by trying to flatten the curve, and thus, reduce LoW of patients in the ED service.
- An intermediate case in which there is the option for patients' relocation is when we can act to improve the system attention.

In this latter situation we will use this value as a reference for the scheduling model and it will be a constraint in the patient scheduling algorithm for non-critical patients, modifying their current arrival pattern in the ED, such that their arrival at the service should lead to a System State in accordance with the calculated system capacity.

5.2 Patients Scheduling Algorithm

Patient relocation consists of the movement of the patient with respect to their initial arrival time in the ED in order to reduce their waiting time and, consequently, the total patients Length of Stay in the service (LoS). Only patients with acuity level 4 or 5 (non-critical patients) can be relocated and we must consider that ThP is the maximum number of patients that can be attended every hour without waiting and that the maximum delay for patient relocation is 6 hours with respect to their initial arrival hour.

Once the system ThP has been established, the algorithm performs the following steps for patient relocation, starting in the hour $i = 23$, and going backwards until the *Initial Hour* is identified, which is the first hour in the System State with a number of patients surpassing the ThP:

- Step 1: Identify holes (free places for patients to move). Move backwards hourly in time, until identifying the first *Critical Hour* (hour with a number of patients surpassing ThP value) in the calculated System State. We also need to identify *Tentative Patients* to be relocated (Figure 5).
- Step 2: According to maximum delay for relocation (6 hours), and under the restriction of ThP in the propagation, remove all possible tentative patients from the identified *Critical Hour* to the corresponding hour for relocation and also create holes removing some more patients if possible. Calculate propagation of patients for the new situation and update System State (Figure 6).
- Step 3: The algorithm goes through these two steps until the *Initial Hour* is reached, and when this happens, the system generates the full update of System State, and also of *Entry Patients*, which is the *Schedule Entry Patients* in Table 4. The *Schedule Patient Limits* in Table 4 indicates the maximum number of patients that should be admitted to the ED each hour.

5.3 Appointment Assignment Policy

The *Appointment Scheduling table* in Table 5 contains all instructions for patient relocation, so that it is the basic tool for recommendation to patients, in addition to the *Schedule Patient Limits*. But an appointment assignment policy is also necessary, which will be based on a first come, first served basis. As shown in Figure 7, all patients are admitted into the service each hour up to the limit of patients' admission in the schedule, as they arrive, and the remaining patients will be recommended to stay at home until the recommended appointment hour for a new admission in the Appointment Scheduling Table.

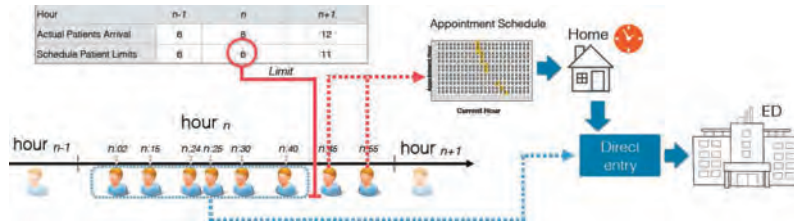


Figure 7: Recommendation system for non-critical patients admission into the ED.

6 EXPERIMENTAL RESULTS

Following the described methodology in Section 5, we proceed with the System State calculation for a specific scenario determined by a patients input with a small overhead in the central hours of the day and a healthcare staff configuration with a ThP of 15 patients per hour. We apply the scheduling algorithm and obtain the fully updated System State after patients relocation and the schedule patients limits in Table 6. The scheduling algorithm also generates the appointment scheduling table in Table 6.

Table 6 : Scheduling Algorithm results and Appointment Scheduling table.

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Calculate System State																								
Historical Entry Patients	4	3	2	2	1	2	2	4	12	13	21	20	16	14	11	11	10	8	7	9	5	3	4	2
System State	4	4	3	2	2	2	3	5	13	16	26	28	24	20	17	16	15	13	11	12	8	5	6	3
Apply Scheduling Algorithm																								
Schedule Patient Limits	4	3	2	2	1	2	2	4	12	12	19	4	5	6	6	7	7	8	7	9	5	3	4	2
Schedule Entry Patients	4	3	2	2	1	2	2	4	12	12	19	7	9	11	12	12	11	11	12	12	10	7	7	2
Updated System State	4	4	3	2	2	2	3	5	13	15	24	14	13	15	16	18	17	16	17	18	16	12	11	5

Appointment Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7 contains the gain in LoW (in minutes) for patients who are discharged after their first visit with doctor (direct patients), patients who need any additional test and those who receive some treatment respectively, after applying the scheduling model for patients admission. This results have been obtained by the analysis of data from a 125 day simulation for the specified scenario showed in Figures 8 to 11.

Table 7: Gain in Length of Waiting after patients relocation.

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Graphical view	Gain %	
Direct Patients	-2	-2				1				6	13	23	17	16	9	8	3	3	-2	-4	-5	-2	-2	-3		28%	
Test Patients	1	1	-1	2			-2		-4	14	44	76	78	70	42	18	15	-1	-4	-2	-16	-17	-10	-3	1		29%
Treatment Patients	-5	4	-18	-2	35	33	43	58	51	88	83	64	59	24	14	5	1	-1	1	-9	-11	13	-5	-1		44%	
Global Gain		-1	-2		3	5	2	5	8	20	31	37	32	24	12	8	1	1	-3	-7	-8	-3	-3	-2		31%	

An overall mean of 31% gain in the LoW of the patients is achieved, and in the particular case of the patients with treatment the average gain amounts to 44%. The highlighted cells in table 7 correspond to hours with a gain above the average. These results prove the efficiency of the model, since its application globally improves the patients' LoW and, therefore, the quality of the provided service in the ED.

Figures 8 to 10 illustrate patients' total length of stay (LoS), showing separately PaT (patient attention time) and LoW of patients in each hour before and after patients relocation for direct, test and treatment patients respectively. Finally Figure 11 shows the global results for all patients.

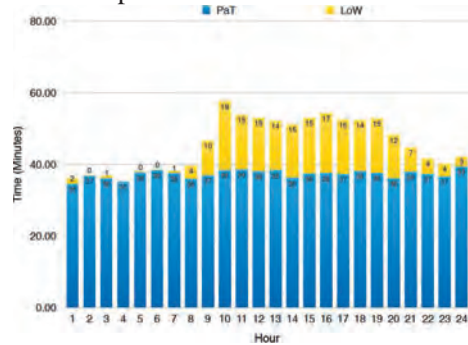
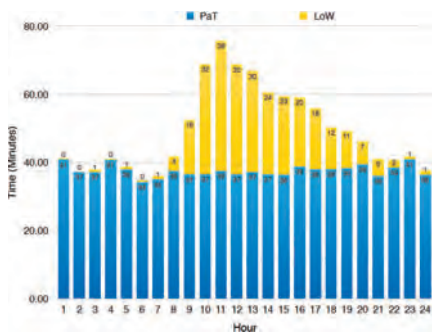


Figure 8: Direct Patients PaT and LoW before and after patients relocation.

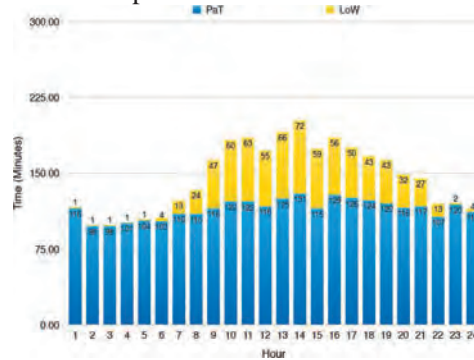
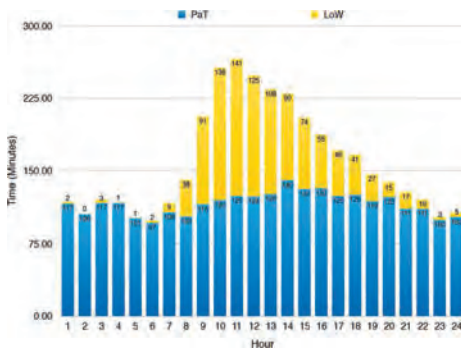


Figure 9: Test Patients PaT and LoW before and after patients relocation.

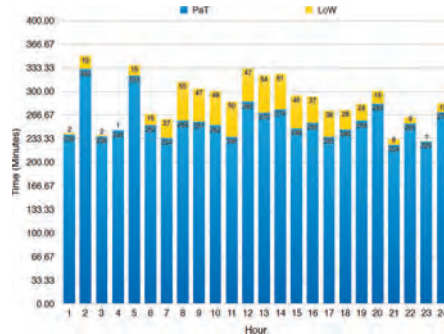
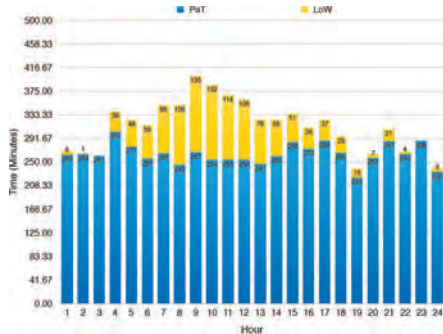


Figure 10: Treatment Patients PaT and LoW before and after patients relocation

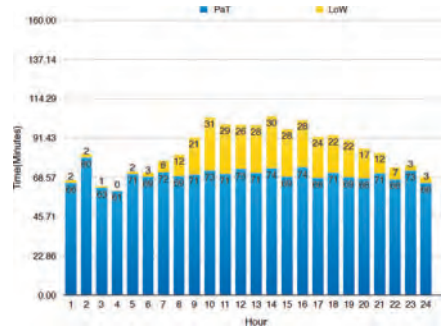
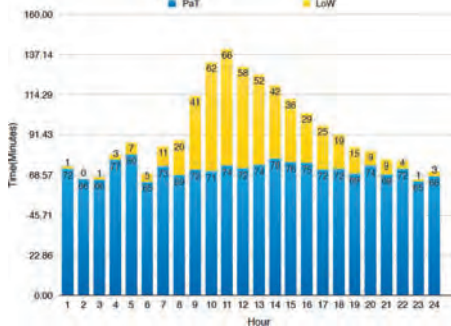


Figure 11: Patients PaT and LoW before and after patients relocation

7 CONCLUSION

The proposed scheduling model for non-critical patients admission into the ED provides a methodology to improve the quality of the provided service and it is helpful to the management of the service to deal with the current growing demand for emergency medical care. The implementation of the model in the ED simulator and the experimental results obtained by the analysis of simulation data prove the efficiency of the model, since it globally improves waiting times in the service, and therefore, quality of care is also improved. However, it should be noted that the implementation of the model in the real system will be efficient to the extent that the proposed recommendation system is also effective on the entry of patients, depending on the decision of the patients, users of the service.

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