Reducing Overcrowding at the Emergency Department Through a Different Physician and Nurse Shift Organisation: A Case Study

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Abstract Overcrowding is a widespread problem affecting the performance of an Emergency Department (ED). In this paper we deal with the overcrowding problem at the ED sited at *Ospedale Sant'Antonio Abate di Cantù*, Italy. Exploiting the huge amounts of data collected by the ED, we propose a new agent-based simulation model to analyse the real impact on the ED overcrowding of a different physicians and nurses shift organisations. The proposed simulation model demonstrates its capability of analysing the ED performance from a patient-centred perspective.
Keywords: emergency department, overcrowding, agent based simulation.

1 Introduction

An Emergency Department (ED) is a medical treatment facility inside of a hospital or another primary care centre and is specialised in emergency medicine providing a treatment to unplanned patients, that is patients who present without scheduling. The ED operates 24 hours a day, providing initial treatment for a broad spectrum of illnesses and injuries with different urgency. Such treatments require the execution of several activities, such as visits, exams, therapies and intensive observations. Therefore human and medical resources need to be coordinated to efficiently manage the flow of patients, that varies over time for volume and characteristics.

A phenomenon that affects EDs all over the world reaching crisis proportions is the overcrowding [12]. It is manifested through an excessive number of patients in the ED, long waiting times and patients Leaving Without Being Seen (LWBS); sometimes patients being treated in hallways and ambulances are diverted [10, 2, 3]. Consequently, the ED overcrowding has a harmful impact on the health care: when

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the crowding level raises, the rate of medical errors increases and there are delays in treatments, that is a risk to patient safety. Not only overcrowding represents a lowering of the patient outcomes, but it also entails an increase in costs [9]. Moreover, the ED overcrowding causes stress among the ED staff, patient dissatisfaction and episodes of violence [6].

Simulation is widely used to test what-if scenarios to deal with overcrowding [12], analysing the use of different resources, setting or policy within the care planning process. Although most of the solutions proposed in literature foresee the use of new additional resources, often they are scarce and there is no economic possibility of new investments [5]. Then human and equipment resources available should be used as efficiently as possible in order to improve the ED processes. For this reason, research addressing short-term decision problems are becoming increasingly in recent years [1]. Placing in the perspective to alleviate the ED overcrowding without changing the ED resources and settings, there are two way to act: (i) changing the human resources planning [13] or (ii) adopting different policies in the allocation of the human and equipment resources [11, 8].

In this paper we deal with the problem of the management of the staff (physicians and nurses) operating at the ED sited at *Ospedale Sant'Antonio Abate di Cantù*, which is a medium size hospital in the region of Lombardy, Italy. Exploiting the huge amounts of data collected by the ED, we propose a new agent-based simulation model to analyse the real impact of a different physicians and nurses shift organisations on the ED overcrowding.

2 Modelling approach

After a brief description of the case study under consideration (more details available in [7]), we report the pre-processing procedure to make the huge amounts of data usable within the simulation model.

The case study. The resources available within the ED are: 4 beds for the medical visits placed in 3 different visit rooms, in addition to one bed within the shock-room and another one in the Minor Codes Ambulatory (MCA), one X-ray machine, 5 Short-Stay Observation (SSO) units (beds), 10 stretchers and 10 wheelchairs to transport patients with walking difficulties. The medical staff is composed of 4–6 nurses and 1–3 physician(s), depending on the time of day and the day of week, in addition to the X-ray technician.

A patient is interviewed and registered as soon as possible by a triage-nurse on his/her arrival in the ED, recording personal data, the main symptom and the urgency code c from 1 (most urgent) to 5 (less urgent). Table 1 reports all the activities that could be performed by a patient within the ED, each one classified into 5 classes (*Triage*, *Visit*, *Tests & Care*, *Revaluation* and *Discharge*). Columns EDc indicate those that are competence of the ED. Columns TS report the timestamps available from the data, that is the start time t_S, the prescription or request time t_P, the report time t_R and the end time t_E.

Table 1 Activities in a patient path

id	description	class	EDc	TS	id	description	class	EDc	TS
A	Triage	Triage	✓	t_E	B	Medical Visit	Visit	✓	t_E
C	Shock-Room	Visit	✓	t_E	D	MCA Visit	Visit	✓	t_E
E	Paediatric Fast-Track	Discharge		t_P	F	Therapy	Tests & Care	✓	t_P, t_E
G	Laboratory Exams	Tests & Care	✓	t_P, t_R	H	X-Ray Exams	Tests & Care	✓	t_P, t_R
I	Comp. Tomography (CT)	Tests & Care		t_P, t_R	J	Echography	Tests & Care		t_P, t_R
K	Specialist Visit	Tests & Care		t_P, t_R	L	SSO	Tests & Care	✓	t_S, t_E
M	Pre-hosp. SSO	Tests & Care	✓	t_S, t_E	N	Revaluation Visit	Revaluation	✓	t_E
O	Hospitalisation	Discharge	✓	t_E	P	Discharge (Ordinary)	Discharge	✓	t_E
Q	Interruption	Discharge		t_E					

Figure 1 depicts a simplified version of the patient path also reporting the human resources associated to each activity: after the triage, a Visit class activity is always provided except for a LWBS patient. Then the patient can be discharged or continue with a sequence of Tests & Care class activities, that is always followed by a revaluation visit, after which the patient can be discharged or go on with other Tests & Care class activities.

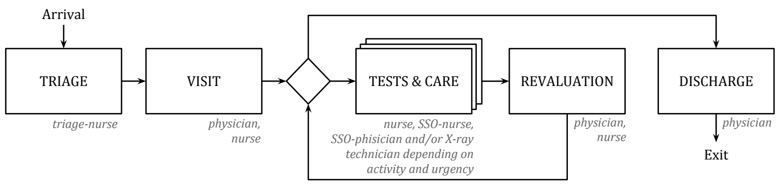

Fig. 1 A simplified path for a patient within the ED and the human resources associated.

Data analysis. In order to supply our simulation model, we are required to pre-process the ED dataset to create an event log, which consists of a set of traces (i.e. ordered sequences of events of a single case), their multiplicity and other information about the single events, such as timestamps and/or durations, resources, case attributes and event attributes. The event log has been generated taking into account the 27 039 accesses of the year 2015. Each case of the event log consists in an access and events consist in activities, which has been classified into 17 event classes corresponding to the activities reported in Table 1.

We should take into account several *noises* in the dataset to estimate start and end time of each activity. In the following, we consider the following 7 noises, that is missing timestamps ($\mathfrak{N}_0$), timely execution ($\mathfrak{N}_1$), forgetfulness in therapies recording ($\mathfrak{N}_2$), multiple recording ($\mathfrak{N}_3$), fake or missing revaluation visit ($\mathfrak{N}_4$), fake medical visit ($\mathfrak{N}_5$), tests reported after discharge ($\mathfrak{N}_6$).

Table 2 Average duration in min of the activities according to the ED staff and estimation of the missing timestamps (✓stands for available).

id	activity duration d	reporting duration r	start time t_S	end time t_E	sorting time $\bar{t}$	id	activity duration d	reporting duration r	start time t_S	end time t_E	sorting time $\bar{t}$
A	5	n.a.	$t_E - d$	✓	t_E	B	15	n.a.	$t_E - d$	✓	t_E
C	15	n.a.	$t_E - t_E^{\text{triage}}$	✓	t_E	D	15	n.a.	$t_E - d$	✓	t_E
E	0	n.a.	t_E	✓	t_E	F	2	n.a.	$t_E - d$	✓	t_S
G	3	15	$t_R - r - d$	$t_R - r$	t_E	H	3	30	$t_R - r - d$	$t_R - r$	t_E
I	10	45	$t_R - r - d$	$t_R - r$	t_E	J	15	45	$t_R - r - d$	$t_R - r$	t_E
K	15	n.a.	$t_E^{\text{last before K}}$	t_R	t_E	L	✓	n.a.	✓	✓	t_S
M	✓	n.a.	✓	✓	t_S	N	1	n.a.	$t_E - d$	✓	t_E
O	1	n.a.	$t_E - d$	✓	t_E	P	1	n.a.	$t_E - d$	✓	t_E
Q	0	n.a.	t_E	✓	t_E						

In accordance with Table 2, the pre-processing algorithm has been implemented as follows with parameters τ and δ fixed to 10 and 30 minutes:

1. Start time and end time of each activity are estimated in accordance with Table 2 ($\mathfrak{N}_0$).
2. A sorting time $\bar{t}$ is fixed for each activity in order to avoid overlapping of activities (because of $\mathfrak{N}_0$); we chose the more reliable time, that is $\bar{t} = t_S$ for activities F, L and M, $\bar{t} = t_E$ for the other ones.
3. If activity E occurs, all the other activities are removed, except the triage ($\mathfrak{N}_5$).
4. The activities of the same path are sorted in chronological order of $\bar{t}$ composing the trace.
5. For each trace, let $\bar{t}_{\text{exit}}$ be the sorting time of the discharge (one among activities O, P and Q) and let $\tau > 0$ be a parameter denoting the amount of time before the discharge in which the forget recording of therapies is remedied. If $\bar{t}_{\text{exit}} - \bar{t}_F < \tau$, then $\bar{t}_F = \max\{\bar{t}_F, t_R^F + 1 \text{ min}\}$, where t_R^F is the prescription time of that therapy ($\mathfrak{N}_2$).
6. For each trace, let $\bar{t}_Y$ be the sorting time of a certain Tests & Care class activity. If $\bar{t}_Y > \bar{t}_{\text{exit}}$, then $\bar{t}_Y$ is fixed one minute before the first revaluation visit after the prescription time of that activity ($\mathfrak{N}_6$).
7. For each activity of each trace, if it precedes the triage time, then it is moved one minute after the triage time ($\mathfrak{N}_1$); if it is not a triage and it precedes the visit time, then it is moved one minute after the visit time ($\mathfrak{N}_1$).
8. For each trace, if there is no revaluation visit between a Tests & Care activity and the discharge, then a fake revaluation visit is inserted a minute before the discharge ($\mathfrak{N}_4$).
9. For each trace, consecutive Tests & Care activities of the same type such that the time between them is less than δ are merged keeping the start time of the first one and the end time of the last one ($\mathfrak{N}_3$).

The simulation model. We propose an Agent-Based Simulation (ABS) model to represent the interactions among patients and medical personnel inside the patient path within the ED by replicating in detail the progress of ED activities. ABS is well suited for modelling such a type of interactions [4]. Five type of agents are implemented as follows:

Decision-maker. A unique agent is used to manage the resource allocation and to assign tasks to the medical staff. When a patient require the execution of an activity, such a request is inserted in a prioritised queue recording the patient ID, the request timestamp, the set of resources needed, the urgency code c and the priority class γ initially equals to c. Every time a new request is made or a resource is released, the agent scans the queue considering the priority, that is (i) patients with lower values of γ first, and (ii) patients with the same value of γ are sorted in decreasing order of the waiting time. When the whole set of resources to provide an activity is available, the agent send a message to the agents representing the patient and the human resources involved in the activity.

Patient. The patient population is reproduced from the event log: an agent is created for each access to the ED from the dataset and relevant information for the replication of its path (i.e. urgency code c, trace, arrival time and several activity durations) are represented by agent attributes. Each agent progresses in their path within the ED replying that in Figure 1 in accordance with its trace.

Physician. Each physician shift is represented by an agent with an attribute that indicates its competence (visit rooms, SSO units, etc.). This agent is characterised by two relevant aspects determined by the end of the shift and the handover between physicians: (i) λ_1 min before the shift end, the agent can be assigned only to urgent patients with $c \leq 2$, or taken over previously; (ii) the last ρ min of the shift models the handover to the next physician (whose agent arrives ε min before starting the shift) in which the agent is no more available for any tasks. Before the handover, the agent waits for a task assignment from the decision-maker agent.

Nurse. The agent is implemented as well as the physician, omitting the handover of the medical records. We denote with λ_2 the min before the shift end in which the agent deal with only urgent patients with $c \leq 2$.

X-ray technician. The agent is implemented as well as the nurse, omitting the limitation on serving non-urgent patients close to the shift end. Since at night-time no technician is working in the ED, we model the on demand technician availability by adding a delay of 30 min to represent the time needed to reach the ED.

The ABS approach allows us to model the continuity of the care process, which is allowed by the ability to identify individual resources (i.e., single physician and nurses) and to simulate their interactions: the same physician is always assigned to a patient for the activities that follow its first medical visit, that is revaluation visits and discharge; furthermore, if the assigned physician ends its shift before the completion of the care process, the activities are performed by the physician to which the medical record has been passed.

Another important aspect represented by the ABS model is the simulation of the behaviour of the human resources during the beginning and the ending of their shift, which are the critical moments that cause a slowdown in the flow of patients. To this end, the parameters ε, ρ and $\lambda_{1,2}$ have been introduced: the arrival of the physician ε min before the beginning of the shift is a common practice to ease the handover made in the last ρ min of the current physician shift; the assignment of non-urgent patients to physicians and nurses $\lambda_{1,2}$ min before the end of the shift is usually avoided to guarantee continuity in the process of care. Finally, to avoid the *starvation* of the less urgent patients, a re-prioritisation of such patients has been planned each υ hours of stay increasing the urgency code c by 1, without going beyond 2 if $c \geq 3$ and 1 otherwise.

3 Quantitative analysis

The dataset of all the accesses to the ED of the year 2015 is used for the analysis in this section. The shifts of the medical staff replicate those of the real case, as reported in Table 3. In last 4 columns the competence of the ED staff are indicated with a check symbol; an asterisk means that the competence is limited to a time slot in which SSO units do not have a dedicated physician. Furthermore, a X-ray technician is available in the ED from 8:00 to 20:00 every day. The model is implemented in AnyLogic 7.3.7. The average computational time for a simulation run is 10 secs.

Table 3 Shifts of the ED staff (real case).

resource		**shift**				**competence**			
type	number	start	duration	weekday	weekend	triage	visits	MCA	SSO
physician	2	8:00	8h	✓	✓		✓		✓*
	2	16:00	7h	✓	✓		✓		✓*
	1	23:00	9h	✓	✓		✓		✓
	1	8:00	8h	✓				✓	✓*
	1	8:00	7h	✓					✓
nurse	2	7:00	7h	✓	✓	✓			
	2	14:00	7h	✓	✓	✓			
	1	21:00	10h	✓	✓	✓			
	2	7:00	7h	✓	✓		✓		
	3	14:00	7h	✓	✓		✓		
	2	21:00	10h	✓	✓		✓		
	1	7:00	7h	✓	✓				✓
	1	14:00	7h	✓	✓				✓
	1	21:00	10h	✓	✓				✓
	1	8:00	8h	✓				✓	

To validate the model, we compare the obtained average waiting times of the patients belonging to 4 urgency classes and the overall, with those computed from the real data. To this purpose we fix $\varepsilon = 15$ min and range υ in $[0.5, 6]$ with step 0.5 h and both λ_1 and λ_2 in $[15, 30]$ with step 5 min. The best fitness has been obtained for the values $\upsilon = 2$ h, $\lambda_1 = 20$ min, $\lambda_2 = 10$ min.

Starting from a request of the ED, a what-if analysis is conducted with the aim of reducing the waiting times of the patients without adding new resources but only changing the time span of the shifts. Table 4 reports the structure of the shifts considered: from the real case (base), we obtain other physician shifts by moving them of 30 and 60 min forward and backward. After selecting the best shift structure for the physicians (phase 1), we repeat the same experiment for the nurse shifts (phase

2). We measure the average waiting times and the average ED Length of Stay (EDLOS) of the patients to evaluate the best configuration: the former is the time elapsed between the triage and the beginning of the first visit, while the latter starts with the first visit and ends with the discharge.

Table 4 Analysing the impact of existing resources: what-if analysis.

	shift		**average waiting time (min)**					**average EDLOS (h)**				
	physician	nurse	1	2	3	4-5	overall	1	2	3	4-5	overall
phase 1	base	base	13	34	76	98	70	8.5	7.5	5.0	4.1	5.4
	+30 min	base	12	34	75	104	71	8.7	7.4	5.0	4.1	5.4
	-30 min	base	37	41	87	117	82	8.7	7.6	5.0	4.1	5.5
	+60 min	base	50	57	95	118	90	9.1	8.2	5.4	4.4	5.9
	-60 min	base	52	61	99	126	96	8.9	8.2	5.5	4.5	5.9
phase 2	base	+30 min	10	31	72	101	68	8.4	7.5	4.9	4.1	5.3
	base	-30 min	36	46	91	120	86	8.6	8.0	5.3	4.4	5.8
	base	+60 min	16	36	77	99	71	8.5	7.6	5.0	4.1	5.5
	base	-60 min	16	35	75	99	70	8.5	7.5	4.9	4.0	5.5

From the results of the phase 1 reported in Table 4, the base configuration seems to be the best for minimising both waiting times and EDLOS. However, most urgent codes could take a slight advantage when the physician shifts are postponed of 30 min. On the contrary, all the other shift configuration worse the waiting times up to 26 min and the the EDLOS up to 30 min in the worst case compared with the base configuration. Regarding the phase 2, the nurse shifts postponed of 30 min can give slightly improvements, that is 2 min for the waiting times and 8 min for the EDLOS on average. On the contrary, the preponing of the nurse shifts of 30 minutes causes a significant worsening of the indices. These results demonstrate the urgent need of additional resources for a significant reduction of the overcrowding. For this reason, we provide a further analysis, in which we evaluate the impact of adding one physician. Starting from the best shift configuration in accordance with Table 4, we analyse the performance inserting a physician shifts with competence on the visit rooms in four different way: (S1) from 8:00 to 16:00 in weekdays, (S2) from 15:00 to 23:00 in weekdays, (S3) from 12:00 to 20:00 in weekdays, and (S4) from 10:00 to 16:00 in weekdays and from 11:00 to 16:00 in weekend.

Table 5 Adding one physician: what-if analysis.

additional	**average waiting time (min)**					**average EDLOS (h)**				
shift	1	2	3	4-5	overall	1	2	3	4-5	overall
none	10	31	72	101	68	8.4	7.5	4.9	4.1	5.3
S1	23	33	74	95	68	8.6	7.4	4.8	3.9	5.3
S2	10	24	58	84	55	8.2	6.9	4.2	3.5	4.7
S3	6	22	56	82	53	8.3	6.6	4.2	3.4	4.7
S4	6	26	65	91	60	8.5	6.9	4.5	3.7	5.0

The resulting average waiting times and the EDLOS are reported in Table 5 proving that an inadequate addition of physician shifts would be useless for the overall performance or even worse, as shown by S1. The best configuration is S3, for which patients wait 15 min less and have an EDLOS 40 min shorter, on average.

4 Conclusions

The proposed ABS model demonstrates its capability of analysing the ED performance from a patient-centred perspective. The change of the existing physician and nurse shifts seems to be insufficient to get a significant alleviation of the ED overcrowding. However the insertion of one physician can reduce the average waiting times of the 24% and the EDLOS of the 14% compared to the current ones.

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