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A DECISION SUPPORT SYSTEM FOR CAPACITY PLANNING IN EMERGENCY DEPARTMENTS

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Abstract
In this article, we present a decision support system (DSS) for improving patient flow in emergency departments (EDs). The core of the system is a discrete-event simulation (DES) model that aims to support capacity planning in the ED, in view of controlling patients' length of stay (LOS). Conceptually, it regards the patient LOS as the result of different queueing systems, the behaviour of which is influenced by different types of capacities. Taking inputs from ED patient record data, the DSS allows to analyse the impact of different capacity changes on patient flow, and to detect efficient capacity combinations using data envelopment analysis (DEA). We report on the insights obtained from a case study in a large regional hospital in Belgium.
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Key Words: Healthcare Management, Emergency Department, Patient Flow, Capacity Planning, Decision Support System

1. INTRODUCTION

Emergency departments (EDs) all over the world are struggling with a phenomenon called *(over)crowding*. While there is no single agreed-upon definition of crowding in the literature, it can be understood in general as "*the situation when the demand for emergency services exceeds the ability of an ED to provide quality care within appropriate time frames*" [1]. Following [2], we chose to use the term 'crowding' in this article. Crowding has received attention since the early '90s in the medical literature (see, e.g., [1-5]) and in the field of Operations Research and Operations Management [6, 7]. Simultaneously, there is increasing pressure on EDs to improve their operational performance, and decrease the length of stay (*LOS*) of patients in the ED [6].

In practice however, hospital management often lacks the tools to effectively analyse the problem and detect efficient solutions. The issue is that EDs are highly complex environments: patient arrival rates vary over time, patient care paths depend on urgency and pathology, resources (staff and beds) may or may not be suited for treating all patient types, urgent patients typically get priority over (and may even preempt resources from) non-urgent patients, patients who need to be admitted often *board* in ED beds (i.e., they remain blocked in ED beds due to the unavailability of beds in the inpatient units (IUs)), etc. While in reality, the patient flow through the ED results from the interplay of all these factors, the majority of academic models tend to analyse only one factor [6]. This article presents a practical DSS for improving patient flow in real-life EDs. It contributes to the literature by:

(1) simultaneously taking into account the main drivers impacting patient flow: (a) limited bed availability in the ED, (b) limited availability of staff (doctors and nurses), and (c) boarding, also referred to as *'access block'* or *'bed block'* [2, 3, 8]. This allows hospital management to analyse the impact of capacity changes (changes in number of beds, staff schedules, boarding times) on patient flow.

(2) taking into account the time-varying nature of the demand and the patient mix (i.e., the patients' pathologies and urgencies).

(3) including a data envelopment analysis (DEA) to detect the solutions that most efficiently reduce patients' *LOS*.

This contribution is important: considering detailed patient mix reveals unexpected results regarding the impact of increased bed (and staff) availability. Going against intuition, increasing bed availability does not always benefit patients. Moreover, the DEA analysis provides a practical tool to detect the 'best' scenario among multiple options. This is further illustrated in Section 4, which discusses the results of the application of the DSS to a large regional hospital in Belgium.

Simulation modelling is a popular tool to analyse and improve healthcare delivery (see, for instance, the review papers [9-11]). Consequently, a vast amount of literature on ED modelling and ED patient flow is available (see, e.g. [12-14] and the many contributions to the Winter Simulation Conference). To the best of our knowledge, however, none of these has simultaneously studied the impact of limited bed availability, limited staff availability, and boarding in view of a comprehensive analysis of patient flow. Moreover, although we found reference to articles employing balanced score cards to narrow attention to the best-performing scenarios [15, 16], the use of DEA seems to be quite novel.

As the patient flow model at the core of the DSS is quite generic (see Section 2), the DSS has the potential to be used in other ED settings, provided the DES is populated with the corresponding input data [14, 17]. Currently, however, the DSS has only been applied to a single case study.

Section 2 gives details on the DSS, along with the input/output requirements. The results of the case study are discussed in Section 3. Finally, Section 4 summarizes the insights and concludes with new research prospects.

2. DSS COMPONENTS

Fig. 1 shows the conceptual patient flow model that forms the core of the DES model (which was implemented using Arena® V.14 by Rockwell Automation), along with the input requirements and the output analysis options. The patient flow model gives a high-level, generic view of ED patient flow, recognizing the three main drivers that influence patients' *LOS* in a general ED: (1) limited bed availability ('wait-for-bed' queue), (2) limited availability of staff ('wait-for-staff' queue), and (3) access block ('boarding' queue).

Upon arrival, patients undergo *triage* to determine their urgency, which will impact their priority for seizing resources (bed and staff) in the ED. After triage, the patient enters the *wait for bed queue*; once he has seized a bed, he enters the treatment phase. This phase typically consists of several process steps. While in treatment, the patient alternates between 2 states: he is either receiving treatment for a given process step or he is *waiting for staff* (i.e., waiting for a doctor and/or nurse required for the next step in his treatment plan). It is the patient's type (pathology) and urgency that determine the probability that he needs to undergo a given step, as well as the actual resources involved and the process time required from each of these resources. The treatment phase can thus be seen as a multi-class queueing system with probabilistic routing, and finite calling population (only patients that have been assigned to a bed can call upon ED staff for treatment). Patients that have been discharged from the ED (i.e., they have finished the treatment phase) either leave the ED immediately or undergo another waiting phase; *boarding*. While patients remain blocked or boarded in an ED bed, they prevent other patients from seizing an ED bed and starting treatment which might lead to ambulance diversion [8], a higher mortality rate [5], higher left-without-being seen (LWBS) rates, and lower profits for the hospital [4].

Note that the different queues in the model are interdependent: an increase in the average time patients spend in the boarding queue and/or the wait for staff queue will, in turn, lead to an increase in the average time spent waiting for a bed (as both factors increase bed occupation). When analysing different capacity options, this interplay is crucial in view of adequately reflecting the impact on patients' *LOS*, as will be demonstrated in Section 3.

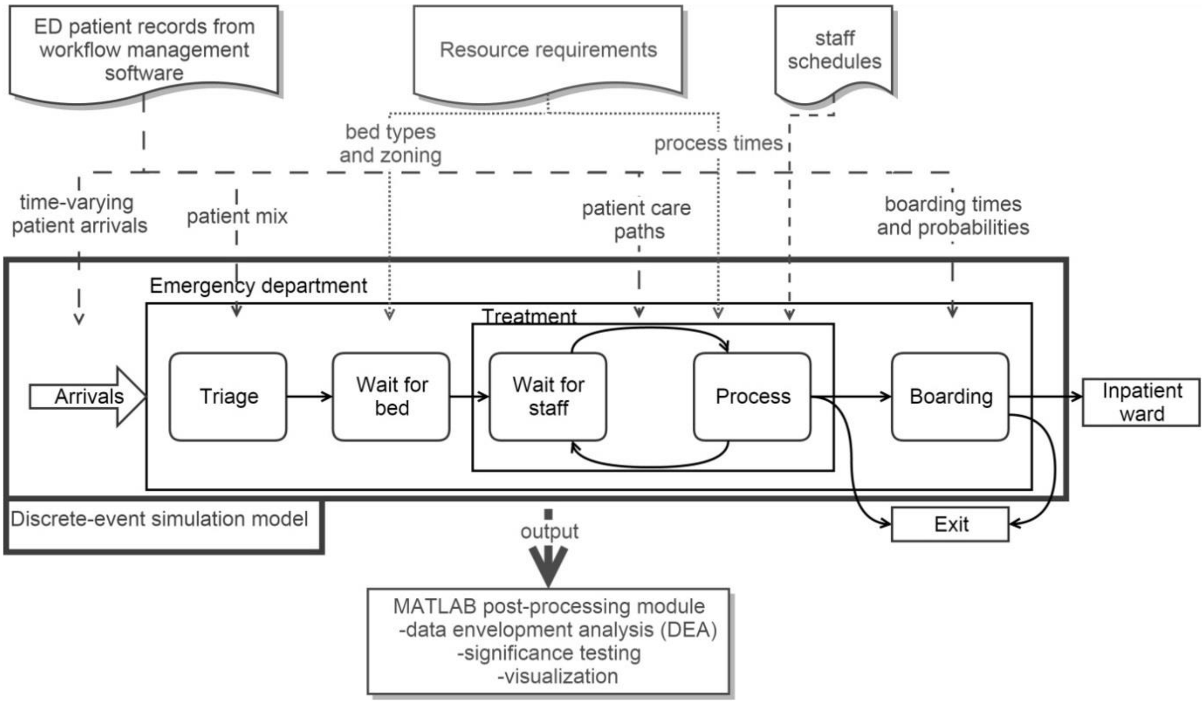


Figure 1: The decision support system (DSS).

As shown in Fig. 1, most of the input requirements can be retrieved from workflow management software that provides detailed ED patient records. This needs to be complemented by information on the resource requirements (such as type of staff needed, time required of each staff member in each step, types of beds needed, and assignment of beds to specific zones in the ED, such as the fast-track zone); obtaining this information requires involvement of ED staff as it is not always tracked in detail in the IT system. Finally, staff schedules need to be taken into account in order to adequately reflect personnel availability over time.

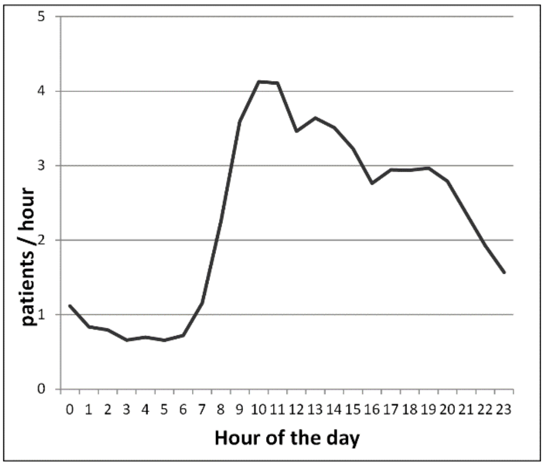
The DES generates several output metrics related to patient flow such as *LOS*, observed wait-for-staff and wait-for-bed times, and ED patient census data. Using the DSS, hospital management can analyse the impact of capacity changes on patient flow (such as adding or changing personnel shifts, adding or switching ED beds, or decreasing patient boarding). A data post-processing module was developed in Matlab, to test if any observed improvements in patient *LOS* are statistically significant. It also visualizes the data outputs in a convenient format, and allows running a DEA analysis on the results.

3. CASE STUDY

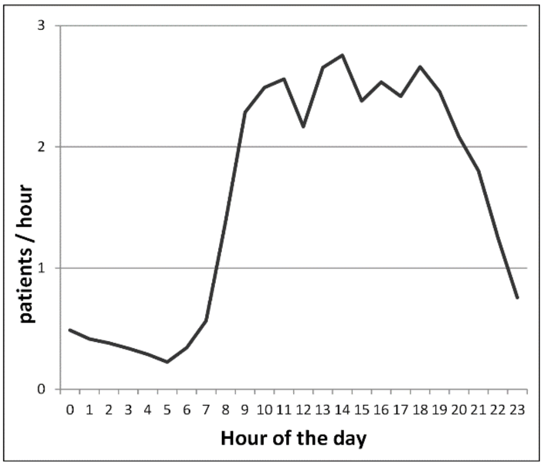
The DSS was applied in the ED of a large regional hospital in Belgium. The ED has 21 beds, and a volume of about 30,000 patients per year of which approximately 33 % need to be admitted to the hospital. The workflow management system used in the ED is E.careED. Section 3.1 first summarizes the main aspects of the model inputs, which were primarily obtained from patient records of the year 2013 (further details on model building and model validation can be found in [18]). Section 3.2 details the experiment, Section 3.3 discusses the resulting insights, and Section 3.4 reviews the applicability of the DSS from the hospital's point of view.

3.1 Model inputs

Two main categories of patients can be distinguished in the ED: No-injury (NI) (i.e., patients with no apparent trauma and intoxication patients) versus Trauma (T) patients (which suffer from injuries such as burns, fractures, bruises, open wounds, luxation, and sprains). These are treated in different zones of the ED (the NI zone versus the T zone).



a)



b)

Figure 2: Historically observed average hourly arrivals of: a) NI patients and b) T patients.

As shown in Fig. 2, the arrival rates fluctuate significantly throughout the day, with a peak period roughly between 10:00 a.m. and 9:00 p.m. As opposed to what has been observed in other articles (see, e.g., [19-21]), no significant seasonal or day-of-week effect could be detected in the data. Upon arrival, patients are categorized further into five urgency classes according to the Manchester triage system [22]: red, orange, yellow, green, and blue (in decreasing order of urgency). In general, the red and orange patients are seen as 'urgent', while the remaining classes are categorized as 'non-urgent'. The changes in patient mix throughout the day were included in the DES model (see [18]).

The two zones each have a prespecified number of treatment rooms (called *boxes*). The T zone has 3 private boxes and 1 shared box (containing 4 beds) for non-urgent patients, 2 private boxes for urgent patients, and an isolation box for aggressive patients (the latter can be used by all urgency categories, in case the other boxes are all occupied). The NI zone has 9 private boxes for non-urgent patients and 2 private boxes for urgent patients. The ED also contains an imaging box, which is shared between the NI and T patients. Urgent patients can seize non-urgent boxes if all urgent boxes are occupied; the reverse is not allowed.

Table I: Process steps in the ED and the required resources.

	Doctor	Nurse	Logistics personnel	External doctor	External personnel
Clinical examination	X	X		X	
Parameters monitoring		X			
Blood sampling		X			
Internal medical imaging		X			X
External medical imaging	X	X	X		X
Internal & external consulting			X	X	
Medication	X	X			
Other examination and treatment	X	X			
Discharge	X	X			

Table I shows the different process steps that may be required on a patient's care path. Routing probabilities could be retrieved from ED patient records, and depend on the patient's type and urgency; estimates for the process time were developed based on judgment from an expert team (comprising doctors and nurses). Doctors, nurses and logistics personnel are ED resources; external doctors and external personnel are not (e.g., the ED can call upon a doctor from an IU for clinical examinations or consulting; external medical imaging personnel can be called upon when needed for specific imaging tasks). Logistics personnel is responsible for transporting patients within the ED (for instance to/from the imaging area). Urgent patients that need more than one resource at a given process step require *collaboration*, implying that all resources (for instance, both a doctor and a nurse) need to be available simultaneously before the process can start. Non-urgent patients do not require such collaboration; resources can be called upon *sequentially*. Urgent patients may preempt ED personnel that are treating a non-urgent patient, effectively interrupting the treatment of that non-urgent patient.

Table II a shows the admission probability which depends on patient type and urgency. As the urgency goes down, the admission probability also tends to go down (as also observed in [23] and [24]), except for the NI Red category of which 'only' 46 % is admitted. This, however, is due to the high mortality rate in this category. The aggregate admission percentage is 33 % (weighted according to the number of patients in each category).

Table II: a) Admission probability and b) average boarding time for patients that are admitted.

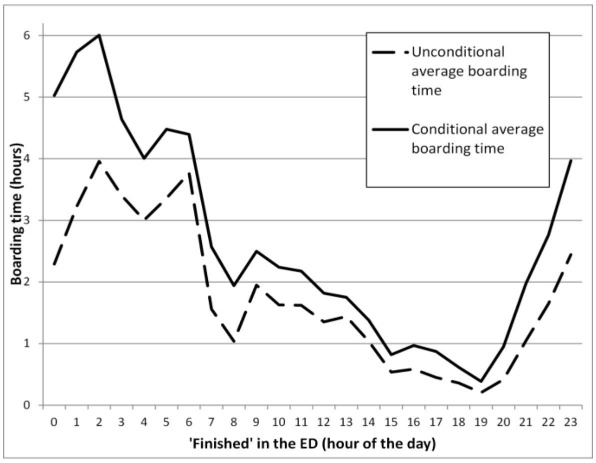
Patient category	Admission probability
NI red	45.5 %
NI orange	79.0 %
NI yellow	60.6 %
NI green	34.9 %
NI blue	21.7 %
T red	93.8 %
T orange	53.3 %
T yellow	17.8 %
T green	2.7 %
T blue	4.7 %

a)

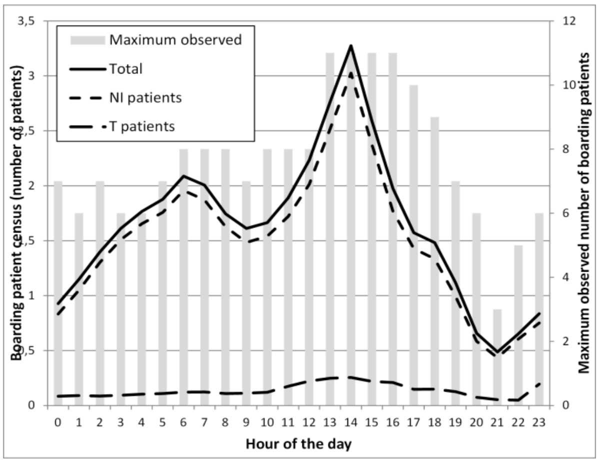
Patient Urgency	Average boarding time (hours)	Number of observations
Red	0.14	28
Orange	1.11	478
Yellow	1.29	1332
Green	1.28	646
Blue	1.45	43
Overall average	1.24	2527

b)

Boarding time depends on the patient type (T versus NI) and the time that the patient finishes treatment in the ED. While there was some evidence that patients with high urgency levels were also prioritized in the admission process to the IUs (Table II b), urgency-specific boarding time distributions could not be fit reliably, especially for the red and blue category (which are very few in number). Overall, the average boarding time for patients that have to be admitted is 1.2 hours.



a)



b)

Figure 3: a) The historically observed expected boarding times of patients that need to be admitted ((un)conditional on whether the patient boards), and b) the historically observed boarding patient census (expected and maximum values).

Boarding times are longest for patients that finish treatment around midnight (see Fig. 3 a). The boarding patient census peaks in the afternoon and around 6:00 a.m. (see Fig. 3 b).

The expert panel in the hospital confirmed that this is due to two protocols that influence patient transfer to the IUs (see Fig. 3):

- The hospital limits the transfer of patients to the IUs during the nights (i.e., between 10:00 p.m. and 7:00 a.m.). Even if there is room in an IU, a patient that finishes treatment at night may have to wait until 7:00 a.m., when regular transportation of patients from the ED to the IUs resumes. Exceptions on the no-night-transport policy are often made in practice for urgent patients or when the ED is very crowded.
- As is common in many hospitals, the hospital starts discharging patients from the IUs after the morning round of the physicians, causing a peak of discharges around 2:00 p.m. [25], explaining the second peak in Fig. 3 b. Overall, boarding patient census never exceeded 11 and the probability of having over 5 boarding patients is only 5 %.

Table III gives an overview of the shift schedule that is currently adopted for ED nurses and doctors; nurses work in 3 shifts (Early, Late and Night) and doctors in 2 shifts (Day and Night). Nurse shifts tend to overlap by 15 or 30 minutes: this overlap is used for briefing. Note that there is no logistics personnel available from 10:00 p.m. until 6:30 a.m.; their tasks are carried out by the nurses at night.

Table III: Current shift structure of ED personnel.

Resource type	Shift type	Hours	Number of resources
Doctor	Day shift	08:00-20:00	2
	Night shift	20:00-08:00	1
Nurse	Early shift	06:30-14:30	5
	Late shift	14:00-22:00	6
	Night shift	21:45-06:45	4
Logistics personnel	Early shift	06:30-14:30	1
	Late shift	14:00-22:00	2
	Day shift	08:00-16:30	1

3.2 Model experimentation

Fig. 4 displays the *LOS* for each patient category, using the inputs that are specified in Section 3.1. This will be further referred to as the *base case* (BC). Evidently, the share of the total waiting time in the *LOS* is larger for less urgent patients. NI patients experience much higher wait-for-bed times than T patients. This observation was confirmed by hospital staff, and is consistent with the historical data: these revealed that full occupancy of NI beds occurred for at least 20 % of the time compared to only 3 % of the time for T beds. Currently, access to a doctor represents the largest bottleneck since patients, on average, wait longest for this type of resource. 'Other' includes triage time and waiting time for logistics personnel and the imaging box, but it is rather insignificant.

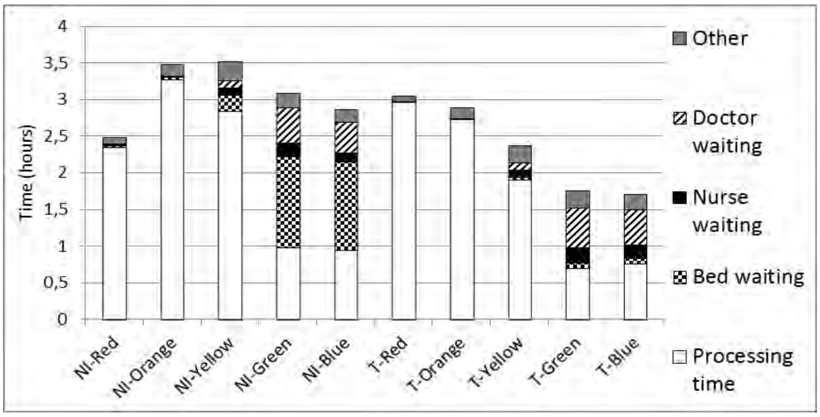


Figure 4: Average *LOS* (excluding boarding time) for each of the 10 patient categories (base case scenario).

We investigated the following scenarios with respect to their impact on patient *LOS*:

- **Evaluation of shift schedule changes:** We analysed 19 shift schedules, that differ from the base case in terms of the possible shift types (with some shifts starting or ending earlier/later) and the total number of doctors and nurses scheduled (see Table IV; the first row refers to the base case scenario of Table III). Notice that scenarios 2 to 6 only include additional nurse hours; the doctor shifts are identical to the base case. The remaining scenarios all have one extra doctor each day, resulting in 48 doctor hours per day.
- **Introduction of *buffer beds*:** This policy relieves crowding by reducing boarding, either by requiring that a number of beds in the IUs are reserved for ED patients [26], or by moving boarding patients to inpatient hallways [27]. Using the DSS, hospital management can analyse *how many* buffer beds are needed to significantly impact patient *LOS*. Alternative options to create buffer capacity are to create an ‘observation unit’ (i.e. a centralized unit for patients that require a longer observation or treatment time but are unlikely to require admission [3, 28]), or a dedicated ‘acute medical admission unit’ (AMAU) or ‘holding area’ [28] for patients that need to be admitted. Regardless of the practical implementation, adding buffer capacity aims to increase the number of ED beds available for patients that still require treatment.
- **Bed switch:** As the base case revealed that the wait-for-bed times are much larger for NI patients than for T patients (Fig. 4), we also investigated the impact of moving one bed from the T zone to the NI zone.

Table IV: Number of nurses and doctors in each shift for all scenarios proposed by the hospital.

Scenario	**Nurse**								**Doctor**					
	Early (BC) 06:30-14:30	Late (BC) 14:00-22:00	Night (BC) 21:45-06:45	Early 08:00-16:30	Early 09:00-17:30	Late 12:00-20:00	Late 13:00-21:00	***Total hours***	Day (BC) 8:00-20:00	Night (BC) 20:00-8:00	Day 06:00-18:00	Day 07:00-19:00	Day 09:00-21:00	***Total hours***
1 (BC)	5	6	4					124	2	1				36
2	4	6	4	1				124,5	2	1				36
3	4	6	4		1			124,5	2	1				36
4 (A)	5	6	4			1		132	2	1				36
5	5	6	4				1	132	2	1				36
6 (B)	6	7	4					140	2	1				36
7	5	6	4					124	3	1				48
8	5	6	4					124	2	1	1			48
9	5	6	4					124	2	1		1		48
10 (C)	5	6	4					124	2	1			1	48
11	4	6	4	1				124,5	3	1				48
12	4	6	4	1				124,5	2	1			1	48
13	4	6	4		1			124,5	3	1				48
14 (D)	4	6	4		1			124,5	2	1			1	48
15	5	6	4			1		132	3	1				48
16 (E)	5	6	4			1		132	2	1			1	48
17	5	6	4				1	132	3	1				48
18	5	6	4				1	132	2	1			1	48
19	6	7	4					140	3	1				48
20 (F)	6	7	4					140	2	1			1	48

3.3 Results and insights

In what follows, we discuss the insights gained from the DES model. All results are obtained by running 20 replications of 200 days for each scenario, with a warmup period of 10 days.

Impact of changes in shift schedule

The post-processing module analyses the changes in patient *LOS* for each alternative shift scenario, and checks whether the observed differences from the base case observations are statistically significant using Paired-*t* confidence intervals. It appeared that none of the proposed scenarios has a significant impact on the *LOS* of the urgent patients. This is in fact not surprising: as shown in Fig. 4, their *LOS* consists mainly of processing time.

Since no significant improvements can be achieved for urgent patients, Table V a only shows the expected decrease in *LOS* for the yellow T and NI patients and the weighted average decrease in *LOS* of the green and blue T and NI patients (using the relative green and blue patient volumes as weights). The decreases are expressed as a percentage of the base case *LOS*. Using the number of doctor and nurse hours as inputs and the average decrease in *LOS* for the yellow and green and blue patients as outputs, a DEA study allows selecting the most efficient shift scenarios for further investigation. In particular, an output-oriented BCC model (first introduced by Banker, Charnes and Cooper in 1978, see in [29]) was used to obtain the results of Table V b. Although Scenario 3 is BCC efficient, we exclude it from further investigation since it did not achieve statistically significant improvements for the blue T patients. Thus, only the BCC-efficient scenarios 4, 6, 10, 14, 16, and 20 (labelled A to F from Table IV onwards) are selected for more detailed analysis.

Table V: a) Performance of the scenarios and b) results of the output-oriented BCC model (scenarios in bold are BCC efficient).

Scenario	**Nurse hours**	**Doctor hours**	**T yellow decrease in *LOS***	**T green & blue decrease in *LOS***	**NI yellow decrease in *LOS***	**NI green & blue decrease in *LOS***
1 (BC)	36	124	0.00	0.00	0.00	0.00
2	36	124.5	0.57	2.49	0.58	2.79
3	36	124.5	0.82	2.90	0.75	3.53
4 (A)	36	132	2.48	10.42	2.33	12.19
5	36	132	2.14	8.64	1.90	10.07
6 (B)	36	140	3.27	13.67	3.30	16.98
7	48	124	1.16	8.50	1.21	8.89
8	48	124	0.91	5.39	0.99	6.63
9	48	124	0.98	6.37	1.11	7.28
10 (C)	48	124	2.20	16.98	2.14	16.51
11	48	124.5	1.82	11.36	1.85	12.35
12	48	124.5	0.49	1.88	0.53	2.35
13	48	124.5	2.11	12.49	2.09	13.40
14 (D)	48	124.5	3.20	20.70	2.91	20.55
15	48	132	3.77	19.83	3.67	22.30
16 (E)	48	132	4.72	26.92	4.48	28.13
17	48	132	3.49	18.38	3.27	20.36
18	48	132	4.55	26.18	4.15	26.92
19	48	140	4.60	22.65	4.63	25.92
20 (F)	48	140	5.60	30.42	5.50	32.38

a)

DMU	**Output enlargement rate**	**Slack nurse hours**	**Slack doctor hours**	**Slack T yellow decrease in *LOS***	**Slack T green & blue decrease in *LOS***	**Slack NI yellow decrease in *LOS***	**Slack NI green & blue decrease in *LOS***
2	1.16	0.00	0.00	-0.16	0.00	-0.07	-0.27
3	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
4 (A)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
5	1.16	0.00	0.00	0.00	-0.38	-0.13	-0.49
6 (B)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
7	1.78	0.00	0.00	-0.15	-1.89	0.00	-0.73
8	2.17	0.00	0.00	-0.24	-5.30	0.00	-2.14
9	1.92	0.00	0.00	-0.32	-4.71	0.00	-2.51
10 (C)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
11	1.57	0.00	0.00	-0.34	-2.82	0.00	-1.11
12	5.48	0.00	0.00	-0.50	-10.41	0.00	-7.68
13	1.39	0.00	0.00	-0.27	-3.33	0.00	-1.92
14 (D)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
15	1.22	0.00	0.00	-0.12	-2.76	0.00	-0.95
16 (E)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
17	1.35	0.00	0.00	0.00	-2.06	-0.05	-0.58
18	1.03	0.00	0.00	-0.04	0.00	-0.21	-0.45
19	1.19	0.00	0.00	-0.13	-3.49	0.00	-1.57
20 (F)	**1.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

b)

Impact of buffer beds and bed switch

We varied the number of buffer beds for each efficient staffing scenario (A to F) and the base case (BC) between 1 and 5 (as discussed in Section 3.1, the probability of more than 5 patients boarding in the ED is very small). Table VI shows for each of these scenarios the resulting average length of stay, waiting time for beds (*WFB*), and waiting time for staff (*WFS*), for different patient categories (as statistical analysis revealed that there is no significant impact on the *LOS* of urgent patients, these are not shown).

Fig. 5 to 7 represent the outcomes of the scenarios with base case staffing (for different numbers of buffer beds, *or* a bed switch), along with the outcomes of the efficient staffing scenarios A to F (with zero buffer beds). The legend used in Fig. 5 to 7 is shown in Table VII. For clarity purposes, these figures only show the impact of buffer beds or a bed switch while using *base case staffing*; the same trends, however, were observed when applying these changes to the efficient staffing scenarios A to F, as evident from Table VI.

Table VI: Average *LOS*, wait-for-bed (*WFB*), and wait-for-staff (*WFS*), as a percentage of the base case, for different scenarios with buffer bed and staff changes.

Staff	Buffer beds	Trauma patients						No-Injury patients					
		Yellow			Green & Blue			Yellow			Green & Blue		
		LOS [%]	*WFB* [%]	*WFS* [%]	*LOS* [%]	*WFB* [%]	*WFS* [%]	*LOS* [%]	*WFB* [%]	*WFS* [%]	*LOS* [%]	*WFB* [%]	*WFS* [%]
BC	**0**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	1	**100**	**106**	**102**	**103**	**108**	**105**	**99**	**75**	**104**	**89**	**68**	**108**
	3	**100**	**115**	**103**	**106**	**118**	**110**	**98**	**53**	**107**	**81**	**44**	**115**
	5	**101**	**117**	**103**	**106**	**121**	**111**	**97**	**48**	**108**	**80**	**40**	**117**
A	**0**	**98**	**61**	**82**	**90**	**58**	**82**	**98**	**84**	**82**	**88**	**80**	**84**
	1	98	61	84	91	59	84	96	58	85	77	50	87
	3	98	65	85	92	61	87	95	38	88	69	29	91
	5	98	64	85	93	62	88	95	33	88	68	25	92
B	**0**	**97**	**56**	**76**	**86**	**50**	**76**	**97**	**78**	**75**	**83**	**71**	**78**
	1	97	53	78	87	50	78	95	52	78	73	44	80
	3	97	53	79	89	52	80	94	32	80	65	23	83
	5	97	54	79	89	52	81	94	27	81	63	19	83
C	**0**	**98**	**55**	**81**	**83**	**52**	**64**	**98**	**82**	**83**	**83**	**75**	**69**
	1	98	57	83	85	55	68	97	61	87	75	51	75
	3	98	65	83	87	60	72	96	42	90	69	32	80
	5	98	67	83	87	60	73	96	38	90	67	28	82
D	**0**	**97**	**40**	**74**	**79**	**39**	**58**	**97**	**77**	**76**	**79**	**69**	**63**
	1	97	44	75	81	41	61	96	56	79	71	45	67
	3	97	49	77	82	43	63	95	37	82	64	27	71
	5	97	50	77	83	45	64	95	33	83	63	23	72
E	**0**	**95**	**25**	**62**	**73**	**22**	**46**	**96**	**67**	**63**	**72**	**57**	**51**
	1	95	26	63	74	23	48	94	46	66	64	35	53
	3	95	25	64	75	23	49	93	28	69	58	19	56
	5	96	27	64	75	23	50	93	24	69	57	16	57
F	**0**	**94**	**20**	**55**	**70**	**17**	**40**	**94**	**61**	**56**	**68**	**51**	**45**
	1	94	18	56	70	16	41	93	39	58	59	30	45
	3	95	19	56	71	15	42	92	22	60	54	15	47
	5	95	20	57	71	15	42	92	18	61	53	11	48

Note: Results displayed in bold are shown in Figs. 5-7.

Table VII: Legend used in Figs. 5, 6, and 7.

Marker for yellow patients	Marker for green and blue patients	Staffing scenario	Buffer beds	Bed switch
○	○	base case	0	
◇	◆	base case	1, 3, or 5	
○	●	A,...,F	0	
$\boxed{B}$	$\blacksquare$ B	base case	0	X

As evident from Fig. 5, switching one bed from the T-zone to the NI-zone tends to slightly increase the *LOS* for the non-urgent T patients, while the *LOS* of non-urgent NI patients decreases. Using base-case staffing, the average *LOS* for all NI patients goes down from 3.2 hours to 3 hours while the average *LOS* for all T patients goes up from 1.8 hours to 1.9 hours. Both differences are statistically significant.

Surprisingly, adding buffer beds does not have the same effect for the different patient types: while NI patients benefit from a significant decrease in *LOS*, T patients may experience a slight increase in *LOS*. This counterintuitive result is also evident from Fig. 5: while introducing extra staff (scenarios A to F) benefits both patient types, adding buffer beds (either 1, 3, or 5) *without* adding extra staff tends to backfire for the T patients. This observation can be explained, though, by looking at the different components of patient *LOS* (more specifically, the wait-for-bed times and wait-for-staff times).

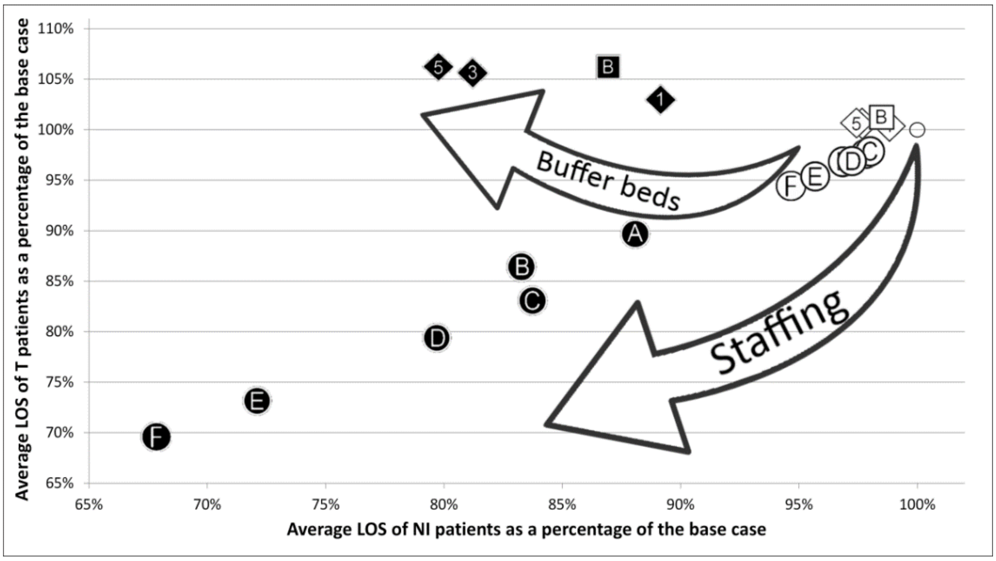


Figure 5: Average LOS as a percentage of the base case for different scenarios.

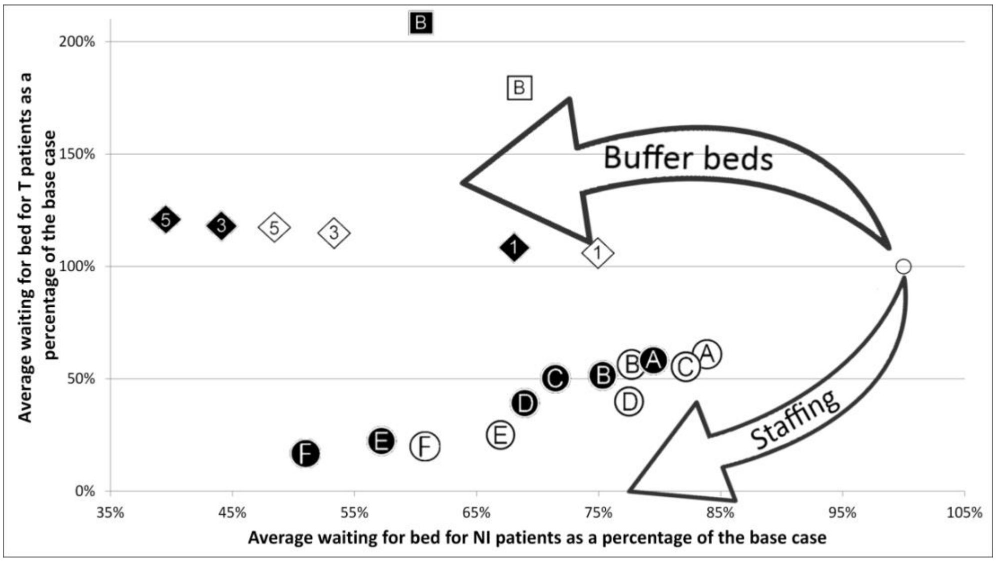


Figure 6: Average wait-for-bed as a percentage of the base case for different scenarios.

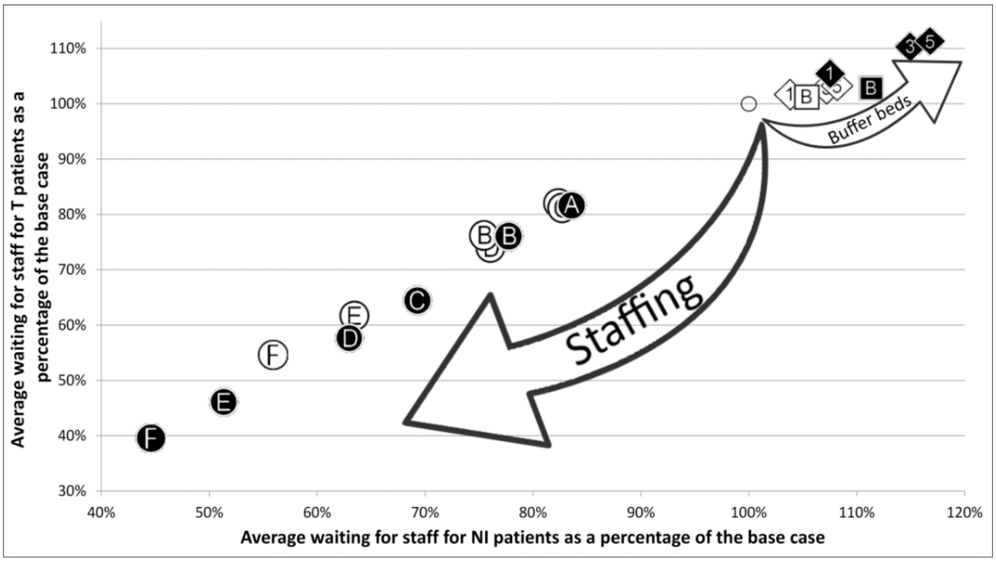


Figure 7: Average wait-for-staff as a percentage of the base case for different scenarios.

Figs. 6 and 7 show that adding staff has a positive influence on both wait-for-bed and wait-for-staff times, as expected. Adding buffer beds, however, tends to *increase* wait-for-staff times (Fig. 7). For NI patients, this increase is offset by a significant decrease in wait-for-bed times (Fig. 6), resulting in a net decrease in *LOS*. The T patients, in contrast, may end up with slightly higher wait-for-staff and wait-for-bed times, resulting in a net increase in *LOS*.

The increase in wait-for-staff times can be explained by realizing that these waiting times result from a queueing network with a finite calling population: only patients that have seized a bed in the treatment area can demand treatment from staff. The size of this pool of patients is limited by the availability of 21 beds. Within this queueing network, the presence of boarding patients tends to *decrease* the load on the staff, since these patients have finished treatment in the ED (though they may require further monitoring and assistance, the workload on ED personnel tends to be lower). As such, more buffer beds (which relieves boarding) actually ensures that ED beds are occupied by patients that require normal treatment, hence increasing the load on the staff, and leading to longer wait-for-staff times.

As significantly more NI patients are admitted than T patients (see Table II a), and the NI-zone seems to have relatively less ED beds than the T-zone (Section 3.2), it is not surprising that adding buffer beds leads to a significant decrease in the wait-for-bed times of the NI patients. For T patients, in contrast, wait-for-bed times tend to increase; ED beds in the T zone do not constitute a bottleneck (as evident from the low wait-for-bed times in the base case), such that adding buffer beds helps little to clear beds. On the contrary, due to the increased workload on staff and the resulting higher wait-for-staff times, wait-for-bed times actually increase (beds are occupied for a longer time by patients still in treatment).

Overall, we can conclude from Table VI that the introduction of buffer beds will only have a beneficial impact on the LOS of *both* T and NI patients when it goes hand in hand with an increase in staffing.

3.4 Evaluation by hospital management

Overall, hospital management perceived the approach provided by the DSS as reliable, truthful, flexible, and useful. The animations used in the DES model increased model credibility and the staff valued the ability of the DSS to display the results in an intuitive, understandable way.

As the results revealed that increased staffing would not benefit the urgent patients, who are the main concern of the ED, hospital management decided *not* to introduce extra doctor or nurse hours. The *LOS* of yellow, green and blue patients are not perceived as an issue.

The explicit insights into the impact of patient boarding, and the possibility to significantly reduce these effects by adding just a few buffer beds, however, led to the implementation of a new policy that automatically *reserves* beds in the IUs for ED patients as soon as the bed occupancy in the hospital crosses 92 %, with the remaining beds being planned for elective patients (this is referred to as a *'code black'*). In that case, elective patients are cancelled to keep beds available for ED admissions (currently, the policy requires that the number of reserved beds covers 50 % of the expected daily admissions from the ED).

A first evaluation of this new policy reveals:

- an increase in patient safety, as newly arriving ED patients can more easily access a bed, and the boarding probability for admitted patients is reduced,
- a decrease in staff stress: while the workload is higher (as predicted by the model), staff utilizations remain at a reasonable level. As a result of the reduction in boarding, staff frustration is much lower than in the past, when boarding patients regularly prevented staff from helping patients in need.

The cost related to this new policy remains limited according to hospital management; it consists mainly of the cost to cancel elective patients when a code black occurs.

Finally, the ED is reducing night-transports to avoid the peak in boarding patients in the morning (Fig. 3 b)), and now regularly allows NI patients to enter the T zone if the NI zone is crowded (as recommended by our 'bed switch' scenario).

4. CONCLUSIONS AND LIMITATIONS

This article presents a DSS for improving patient flow in EDs. Based on a generic patient flow model, the system allows to analyse the impact of different capacity changes on patient flow and to study how the different subsystems influence each other. The DSS results indicate that the dynamic behaviour of the patient flow in the ED (and the resulting patient *LOS*) is governed by different feedback loops:

1. a positive feedback loop between the number of buffer beds provided, and the wait-for-staff times.
2. a negative feedback loop between the number of buffer beds, and the average time that patients spend boarding in an ED bed.
3. a positive feedback loop between both boarding time and wait-for-staff time on the one hand, and wait-for-bed times on the other hand (as both influence the utilization of ED beds).

The key theoretical insight is that reducing boarding may increase the workload for ED staff, and is likely to increase wait-for-staff times. This feedback loop thus impacts the net effect of anti-boarding measures on patient *LOS* (when the feedback loop is ignored, the effect on *LOS* is likely overestimated). As observed in the case study, reducing the boarding times may even *increase* the *LOS* of some patient categories. In spite of the many research articles that have focused on patient flow in the ED, none of them currently encompasses all aspects to include these feedback loops; most focus *either* on scheduling, *or* on boarding times. In most analytical approaches, the wait-for-bed and wait-for-staff components are not even modelled separately: arriving patients immediately queue for staff. The aspect of the finite calling population, which is a key for feedback loop 1, is thus not included. The DSS proposed in this article explicitly takes into account the interaction between the different queues, resulting in more realistic flow time estimations. Currently, the DSS has only been applied to a single case study. Though we are confident that it has the potential to be used also in other ED settings (as wait for bed, wait for staff and boarding are inherent components in many real-life EDs), more applications are required to further validate and fine-tune the system.

The application of the DSS to the case study revealed that, in spite of the presence of workflow management software, the possibilities of the software are not used to the fullest extent (for instance, in the case study, the software was not used to log processing time data). Consequently, the analysis of the input requirements for the DES model in the case study was quite time-intensive. While options exist to reduce the effort of building the DES (e.g., by making simplifications, modifying an existing model or using a generic model), these options typically limit the level of detail that can be achieved, and may make it harder to get support and involvement from the ED staff and hospital management [14, 17].

In future research, we intend to develop an optimization module that enables the DSS to pro-actively propose scenarios that improve a certain goal function (for instance, the weighted average *LOS* of the different patient types) while meeting given constraints (e.g., shift schedule constraints). Given the complexity of the typical ED environment, this will likely require the development of a heuristic approach. Alternatively, metamodelling approaches (such as in [30]) may be used.

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