Effect of different patient peak arrivals on an emergency department via discrete event simulation: a case study

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Abstract
Emergency department (ED) overcrowding is a well-recognized worldwide phenomenon which affects the quality of emergency care. A direct consequence of overcrowding is a long wait for visit and treatment of people who require primary care, possibly endangering the lives of critical patients. Healthcare management literature devoted to analyze ED operational policies is very wide, and many approaches have been proposed to address this important problem. However, less attention has been given to patient peak arrivals caused by the occurrence of some critical events which can strongly strain the operational efficiency of an ED. In this paper; we consider the particular case study of a medium-size ED located in a region of Central Italy recently hit by a severe earthquake, aiming at assessing the effects of such an occurrence on the ED operation. In particular, we propose a discrete event simulation (DES) model to analyze the patient flows through this ED, simulating unusual operational conditions due to a critical event, like a natural disaster, which causes a sudden spike in the number of patient arrivals. The availability of detailed data concerning the ED processes enabled building an accurate DES model and performing extensive scenario analyses. The model provides a valid decision support system for the ED managers in assessing specific emergency plans to be activated in case of mass casualty disasters.

Keywords
Emergency department, discrete event simulation, patient flow, overcrowding, patient peak arrivals

1. Introduction
Emergency medical service (EMS) represents one of the most important healthcare services, considering that it concerns people’s lives. The recent survey paper by Aringhieri et al.¹ reports a comprehensive review on EMSs and introduces the novel concept of emergency care pathway (ECP). Following the new patient-centered approach that focuses on patients rather than caregivers, the ECP considers the whole healthcare chain, composed of several steps (namely the appropriate sequence of activities), aiming at growing patients’ safety and gratification. Relying on ECP, the entire emergency care delivery system is considered instead of single EMSs, thus enabling optimal allocation of the resources requested along the whole pathway. Of course, to this purpose, an effective interaction among ECP stakeholders is needed to guarantee timeliness and fairness of the delivered services.

Emergency department (ED) represents the entry point of the ECP, and its operational efficiency is fundamental for providing healthcare services to people who need urgent medical treatments. An ED is open 365 days a year and 24 h a day, and people with different urgency arrive requiring treatment. Since the services delivered by an ED are time-critical, the main issue concerns the response time. Unfortunately, the well-known and growing problem of overcrowding tends to enlarge the waiting times (WTs), endangering the life of critical patients. Today, the overcrowding is an international phenomenon widely considered in the specific literature.²-⁴ In particular, according to Hoot and Aronsky,² possible causes of overcrowding are

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insufficient staff, shortcomings of the structures, flu season, request of nonurgent treatments, and unavailability of hospital beds. Besides treatment delays, other possible consequences of overcrowding are reduced quality of the services, higher patient mortality, ambulance diversion, growing number of patients who leave without being visited, and greater expenses for the service provider due to longer patient stay. Moreover, negative issues due to overcrowding are greatly amplified whenever mass casualty disasters occur. In this case, the rate of patient arrivals suddenly increases and some different tactical and strategic decisions must be adopted to ensure timely treatments. It is worth noting that an overcrowded ED may have a negative impact on the downstream units, too. In fact, after treatments in an ED, patients who are hospitalized are transferred to an appropriate hospital ward, to the intensive care unit (ICU), or to the intermediate care unit, i.e., the step-down unit (SDU).5,6

In this paper we propose a DES-based approach for analyzing a particular case study: the operation of an ED of a medium-size hospital located in an Italian region where the recent earthquakes have put a strain on the EDs of the area. For such an ED, it is crucial to assess the impact of unusual/critical events which cause peak arrivals to design suited contingency plans. We study the effects of spikes in the number of patient arrivals on the ED operation. The availability of detailed data concerning the ED processes allowed us to build an accurate DES model, well reproducing the actual ED operating modes. After a complete input analysis and the accurate construction of a conceptual model, we implemented it by using ARENA 16 Simulation Software7,8 which is one of the most commonly used general purpose DES packages. Based on flowchart modules, it enables building the simulation model and performing input analysis, simulation runs, and output analysis. The model has been accurately verified and validated to guarantee that it is an accurate representation of the system under consideration. Several scenario analyses have been performed, aiming at evaluating the impact of possible changes in the ED operating conditions. We focused on assessing the main ED key performance indicators (KPIs) under different critical scenarios.

Patient peak arrivals can be of different patterns, and they seriously affect the ED operation. We experienced some artificial scenarios we have specially created trying to reproduce really occurred situations. The model we propose is very helpful for the ED managers both in the daily management of the resources and in the assessment of suited emergency plans to be adopted in case of critical events.

The paper is organized as follows: Section 2 reports some background material and a literature review. In Section 3, generalities on operating conditions of Italian EDs are briefly reported. Section 4 describes the case study of the ED we consider. In Section 5, we detail the DES model we propose, along with the input analysis and the model verification and validation. Section 6 reports results for the “as-is” status along with extensive scenario analyses, mainly focused on peak patient arrivals. Finally, some concluding remarks are included in Section 7.

2. Background

In the recent years, techniques from operations research have been frequently applied for tackling the problem of overcrowding of EDs. Since 2005, the National Academy of Engineering and the Institute of Medicine have highlighted the importance of using tools from operations research and systems engineering (statistical process controls, queuing theory, mathematical modeling and simulation) in healthcare delivery, to improve performance of care processes or units.9

It is well known that complexity and high variability of the processes related to healthcare delivery in most cases make the application of standard techniques very difficult. Simulation is considered of fundamental importance for analyzing several healthcare settings (see, e.g., Reid et al.9 and the several examples reported therein and Almagossi10). In particular, simulation models have been widely applied to EMS operations (see Aboueljinnane et al.11 for a survey). Several papers in the simulation literature are devoted to study the patient flow through an ED by means of discrete event simulation (DES) models11–18 and agent-based simulation (ABS) models.19–23 In particular, DES has been extensively used for studying causes and effects of ED overcrowding. We refer to Paul et al.24 (and to the many references reported therein), and to the more recent paper by Nahhas et al.,25 for a review of simulation studies available in the literature devoted to the ED overcrowding phenomenon and for a discussion on the effectiveness of using DES models. Among the many papers which deal with ED overcrowding, we mention Wong et al.,17 where an ED in Hong Kong is simulated to assess how modifying the path of the patient clinical process and the level of resources affects the performance; Joshi et al.,14 where the simulation model is used to understand the process which allows shortening the WTs and the length of stay (LOS) by varying the workload among staff members and by giving nonurgent patients the possibility of returning afterwards; the many papers addressing the adoption of fast track systems in the ED, such as Kuo et al.,26 and Aroua and Abdulnour,27 which propose to send less urgent patients to specific queues so that they receive the service early, and hence, they will be discharged earlier; Whitt and Zhang,28 where an in-depth study on patient interarrivals and length of stay in an ED located in Israel is reported; and Daldoul et al.,29 where a stochastic model is considered to reduce the average total patient WT in a university hospital. From the wide literature on
3. Generalities on EDs and Italian guidelines

The ED consists of two categories of stakeholders: care providers (physicians and nurses) and patients needing a specific care. Moreover, there are physical resources, such as beds, machineries, stretchers, and so forth, necessary to host and visit patients during their stay. Each patient arrived to the ED goes through different clinical paths. This flow comprises several steps which generally consist in the triage, whose aim is to assign an urgency code to every patient, medical visits, examinations, reassessments, and, finally, the leaving of the ED, with diverse kinds of discharge.

As a first step, a triage tag is assigned to every incoming patient, to determine the priority of treatment. Different systems of classification are usually adopted. The most commonly used scale in Italy is reported in Table 1. Moreover, in some regions, a blue tag is also used as intermediate case between green and yellow tags. In some countries, more fine-grained (sometimes numerical valued)
scales are adopted. To guarantee more appropriate clinical paths and following the main current international scientific evidence, the Italian Ministry of Health is going to adopt new guidelines. They are based on a new triage which considers five numerical urgency codes\textsuperscript{49,50} as detailed in Table 2. This classification closely resembles the Emergency Severity Index (ESI) adopted in the United States, which is based on an algorithm that rapidly yields grouping of patients into five classes, as described in Gilboy et al.\textsuperscript{51}

After assigning the triage code, the more appropriate Diagnostic-Therapeutic Care Path (DTCP) is activated. In particular, a patient can be sent (1) to an ED room, (2) to outpatient facilities, (3) toward a “Fast Track,” and (4) to the “See and Treat” service. The fast track and see and treat are novel services recently introduced to reduce the WTs, the LOS in the ED, as well as the percentage of patients who leave without being seen (LWBS). The patients directed to ED rooms follow different clinical pathways which include medical examination and diagnostic tests up to the definition of the outcome. The patient flow inside ED rooms is very complex, due to the many and different specific needs (often even difficult to identify in a short time) and the high variability of medical conditions of the incoming patients. Moreover, the flow is also strongly affected by the availability of the resources such as staff on duty, number of rooms and machinery dedicated to different services, capacity of holding areas, and beds for hospitalization.

The ED process is usually characterized by the following outcomes: discharged home with reliance, if necessary, on territorial structures which provide control at outpatient facilities; hospitalization at an hospital ward (if a bed is available) or transfer to another hospital; admission to the short stay unit (SSU) (whenever such unit exists). The SSU is an inpatient unit attached to the ED, managed under the clinical governance of the ED staff, designed for the short-term treatment, observation, assessment, and reassessment of patients. When a patient is discharged at the end of the clinical pathway, a physician assigns an exit code corresponding to the outcome.

Unfortunately, very frequently, the great number of incoming patients leads to overcrowding of an ED, which is a worldwide phenomenon and it is well perceived by the stakeholders: long patient WTs before the medical examination, excessive number of patients in the ED, and high percentage of patients who LWBS are clear indications of such problem. To give a formal assessment of the degree of overcrowding, some measures have been proposed. They enable monitoring the state of the ED, describing the current situation, and they can also work as alarm bells to avoid reaching a critical level. The most commonly used are the Real-time Emergency Analysis of Demand Indicators (READI), the Emergency Department Work Index (EDWIN), the Work Score, and the National Emergency Department Overcrowding Scale (NEDOCS). They are continuous valued indicators computed on the basis of some operational variables which enable us to quantify the degree of overcrowding of an ED (see Hoot et al.\textsuperscript{52} and the references reported therein for the definition of these methods of measurement). However, the study reported in Hoot et al.\textsuperscript{52} showed that none of these measures actually provides a reliable predictive analysis at a low percentage of false warning.

To analyze (and to possibly prevent) the overcrowding phenomenon, it is necessary to detect the time spent by the patient inside the ED, during the different phases of the whole process. To this aim, novel Italian guidelines recommend monitoring the times of the clinical pathway in relation to the assigned priority codes. In light of these guidelines, a great interest is shown by the ED managers in tools which enable performing scenario analysis, like those provided by DES. The aim is to assess how the main KPIs change after possible redesigning of ED patient flows and changing of the model of care.

A great and increasing interest concerns the use of simulation modeling for studying the impact of patient arrival surges caused by some disaster. The related Italian guidelines state specific measures to be adopted to efficiently tackle such situations. In particular, the so-called “Internal Emergency Plan for Massive Inflow of Injured” (in Italian, Piano di Emergenza Interno per il Massiccio Afflusso di Feriti (PEIMAF)) has been issued in recent years. In this plan, different critical levels have been provided, and suited operative measures are indicated to reallocate ED human and physical resources, whenever it is activated due to critical events. Moreover, low-complexity patients can be addressed to outpatient facilities to enable the ED staff to timely deliver the most urgent treatments. The application of such an emergency plan occurred in Genoa, Italy, on 14 August 2018, when Morandi’s Polcevera viaduct collapsed, causing 43 deaths and many injuries and, more recently, in many Italian EDs for the maxi-emergency due to COVID-19 pandemic.

### Table 1. Color coding scheme for triage of incoming patients.

| Tag       | Description                                                                 |
|-----------|-----------------------------------------------------------------------------|
| Red tag   | Very critical, danger of life. The patient must be visited immediately       |
| Yellow tag| Fairly critical, high risk. The patient should be visited as soon as possible |
| Green tag | Minor injury, no risk of conditions worsening. The treatment can be delayed.  |
| White tag | No injury, minimal pain with no risk features. The treatment can be deferred. |
4. The case study: the ED of the “E. Profili” Fabriano hospital

In this section, we detail our case study concerning the ED of the “E. Profili” Fabriano (Ancona) hospital. This hospital is located in the Italian region of Marche, and the catchment area covers about 48,000 inhabitants. Every year, about 27,000 patients arrive at ED requiring medical assistance; hence, it can be considered of medium size. A detailed understanding of the ED operation was gained through the process mapping we performed assisted by the ED staff. In the sequel, we report a brief description of the ED rooms and staff; moreover, we summarize the patient flows through the ED. This ED is composed by

- A triage area, where a nurse assigns the color tag at each incoming patient and it can host one patient at a time;
- A waiting room where patients queue for the triage and (after the triage) they wait for the medical examination;
- Three areas for medical treatment:
  - Area A: the shock room for red tagged patients;
  - Area B: the room for green and white tagged patients;
  - Area C: the room for yellow tagged patients.
- A holding area;
- An SSU.

As regards the areas for the medical treatment, Area A (the shock room) is the most equipped one, and two critical patients can be hosted simultaneously. In Area B and in Area C, one seat is available. During the night (9:00 p.m.–8:00 a.m.), only Area A and Area B are in operation, so that also yellow tagged patients are visited in Area B. As regards the ED staff, physicians and nurses are on duty according to the shifts reported in Tables 3 and 4.

As regards the patient flow, arrivals are by ambulance or autonomously. After the registration at the check-in desk, all the incoming patients are admitted to the triage area where a nurse collects patient’s health information and assigns the color tag. Critical patients arriving by ambulance are directly transferred to a medical area for immediate treatment, without going through the triage area. After the triage, a patient waits for the call in the waiting room where the estimated WT is displayed on a screen. Then the patient is transferred to an appropriate area inside the ED for medical visit according to the assigned color tag. In severely urgent cases (red tags), the patient is examined in the shock room (Area A) for possible immediate treatments. In less severe cases, physicians, after performing health assessment, decide the clinical pathway which must be followed by the patient, possibly changing the color tag assigned at the triage. The pathways can be very differentiated on the basis of the acuity of patient’s illness. In many cases, the physician requires additional examinations for the patient (e.g., clinical laboratory tests, X-ray, electrocardiogram). In other cases, patient is transferred to the SSU for a short observation. Moreover, patients with less serious illness and single specialist relevance are assigned to the fast track service, namely a specific area of the ED provided by a multidisciplinary team, where timely patient treatment and discharge are ensured.

Physicians and nurses are shared among all the areas of the ED, including the reassessment area, and they move among different areas based on needs. One physician and one nurse manage the visit and the treatment of one patient. If a red tagged patient arrives and all the physicians on duty are busy, the less urgent patient treatment (corresponding to the less severe priority tag) is interrupted for immediate treatment of the red tagged patient. The less urgent treatment is then resumed at a later time. Note that this “preemptive-resume” service scheme is adopted only in the case of red tagged patient arrivals; in the other cases, patient join a waiting queue. A similar scheme is adopted for nurses, to guarantee immediate treatment of red tagged patients.

Whenever additional examinations are requested, patients are brought to specific laboratories. When the related diagnostic reports have been issued, a reassessment of the patient is performed by the physician, who can require further examinations and/or an additional
observation period. At the end of the pathway, the final diagnosis is delivered and the patient is discharged from the ED. When a patient is discharged, a physician assigns an exit code corresponding to the outcome, to identify the patient’s clinical severity level. Furthermore, a detailed description of the outcome must be issued. The outcome is encoded according to the following list:

- **O1**: patient is discharged home;
- **O2**: patient is discharged home with reliance on outpatient facilities or family physician;
- **O3**: patient is hospitalized at a hospital ward;
- **O4**: patient is transferred to another hospital due to bed unavailability at the appropriate ward of the hospital;
- **O5**: patient refuses hospitalization and leaves the ED despite the medical request;
- **O6**: patient leaves during examinations, i.e., the patient does not complete all the required tests and abandons the ED without informing the staff;
- **O7**: patient leaves without being seen, i.e., the patient abandons the ED waiting room before being examined by a physician (LWBS);
- **O8**: patient dies during the stay at the ED;
- **O9**: patient has arrived deceased to the ED.

To perform a complete process mapping of the ED, many interviews have been carried out to the staff (physicians, nurses, managers) and direct observations took place. Moreover, all the available data concerning patient flow during February 2018 have been anonymously collected. We chose February because, according to interviews to the ED staff, it is one of the most representative months regarding the functioning of that ED. It is in fact a month that includes requests related to the winter season, not affected by holidays (such as December and January), thus reflecting a standard workload of the ED of that period. If data were available over several months, our current model could be easily extended to take into account different seasonal patterns. However, our work is focused on the effect of a sudden peak of the patient arrival rate which can intervene at any time of the year, overlapping the standard patient arrivals of that time. Especially in the extremely loaded scenario described in Section 6, actually if the sudden increase in the arrival rate considered is very large, we expect the results to be slightly affected by changes in the standard patient arrival rate due to seasonality.

From 00:00 of February 1 to 23:59 of February 28, 2018, the overall number of patients arrived to the ED is 2046. The timestamps recorded are reported in Figure 1. They have been extracted and organized in a suited database. Note that, since the *holding area* and the *SSU* are not subject of our study, these two units of the ED are not specified in our model, and hence not represented in Figure 1. In Table 5, we report the number and the percentage of color tags assigned at the triage on arrival. Moreover, we also report in Table 5 the number and the percentage of patients LWBS. Finally, the number and the percentage of deceased patients is

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**Figure 1.** Collected timestamps for the ED process.

**Table 5.** Number and percentage of color tags assigned at the triage at incoming patients (Columns 2–3), number and percentage of color tags on discharge (Columns 4–5), and percentage of patients LWBS (Column 6).

| Triage tags | T ags on discharge | LWBS (%) |
|-------------|--------------------|----------|
| White       | 149                | 171      | 4.65     |
| Green       | 1448               | 1612     | 1.61     |
| Yellow      | 434                | 243      | 0.41     |
| Red         | 15                 | 18       | –        |
| Deceased    | 2                  | 2        | 0.1%     |

LWBS: leave without being seen.
in Table 6, it is clear that some color tags are changed to another tag (always an adjacent tag).

In Table 6, we report the distribution of patients on the basis of the tag on discharge and according to the list of the outcomes.

| O1 | White | Green | Yellow | Red | Total |
|----|-------|-------|--------|-----|-------|
|    | 121   | 1025  | 23     | 1169|       |
| O2 | 39    | 496   | 21     | 556 |       |
| O3 | 29    | 182   | 14     | 225 |       |
| O4 | 4     | 4     | 8      |     |       |
| O5 | 19    | 10    | 29     |     |       |
| O6 | 3     | 17    | 2      | 22  |       |
| O7 | 8     | 26    | 1      | 35  |       |
| O8 | 2     |       | 2      |     |       |
| O9 |       |       |        |     |       |
| Total | 171 | 1612 | 243 | 20 | 2046 |

Table 7. Probability distribution of visit times and additional examinations and reassessments times.

| Visit    | Exams and reassessments |
|----------|-------------------------|
| White    | Lognormal(7.87, 9.77)   | Weibull(23.5, 0.643) |
| Green    | Lognormal(12.7, 11.6)   | Weibull(64.2, 0.549) |
| Yellow   | 3 + Erlang(6.39, 3)     | 29 + Weibull(183, 0.635) |
| Red      | 11 + 39 Beta(0.673, 1.30) | 0.999 + Exp(69.3) |

resources needed for immediate treatment of the red tagged patient.

An entity corresponding to not critical patient undergoes the triage process and receives a color tag as entity attribute. Then, the entity joins the queue of the waiting room, waiting for the visit. During the wait, an entity may possibly leave (Outcome O7). Entities waiting for the visit are selected from the queue on the basis of the priority (the color tag), and first-in, first-out (FIFO) criterion is used within each priority class, i.e., for entities with the same color tag. At the beginning of the visit, one physician, one nurse, and one seat in the corresponding area are seized. The duration of the visit is assigned by the probability distributions reported in Table 7, depending on the entity color tag. During the visit, the DTCP for the patient is decided, possibly changing the entity color tag assigned at the triage. A change of the color tag implies that the entity will be handled as a new-color tagged entity in all the downstream modules. After the visit, an entity can be sent to many different segments of the model. In less severe cases, an entity leaves the system (the patient is discharged) for Outcomes O1 and O2.

The phases following the visit are additional examinations and reassessments. In our model, they are represented by a single process whose overall service time is given by means of the probability distributions reported in Table 7. Note that all possible further treatments are considered in this module since the service time also includes duration of all treatments and reassessments after visit. At the end of the DTCP, the entity is discharged from the system model, according to the proper outcome.

In this summary description, for the sake of brevity, a number of specific issues implemented in our model are not reported. In fact, in our model, we also take into account some details we have become aware of by interviewing ED personnel, e.g., the setup times needed for environmental sanitation of the ED areas at the end of each visit. Moreover, note that the choice of using a single process module to represent additional examinations and reassessments is motivated by the availability of only timestamps $t_5$ and $t_6$ (see Figure 1). This reflects the well-known difficulty in modeling such phases due to both their
high variability and lack of specific timestamps of the activities involved. A simplified logic diagram of the simulation model is reported in Figure 2. We implemented the simulation model by using ARENA 16 (64 bit) Simulation Software.\textsuperscript{7,8}

As regards the KPIs of interest, to meet specific demand of the ED managers, we focus on the analysis of the patient flow starting from the end of the triage and, in particular, in monitoring, for each color tag,

- The \textit{waiting time} (WT) between the end of the triage and the starting of the visit, namely $t_2 - t_1$ in Figure 1;
- The \textit{total time} (TT) after the triage, i.e., the time between the end of the triage and the discharge, namely $t_5 - t_1$ in Figure 1.

These indicators are very similar to “door-to-doctor time” and “door-to-disposition time” metrics used in literature\textsuperscript{53,54} with the only difference that triage time is not included in WT and TT. As already mentioned, this choice is motivated by the practitioners’ request of focusing on all the processes following the triage phase. But, on the other hand, triage is usually carried out as soon as patient arrives and triage duration is usually negligible with respect to waiting and treatment times. Therefore, similarly to door-to-doctor time, waiting time WT is a very important component of ED throughput, having strong implications with the percentage of patients who LWBS.\textsuperscript{55} Moreover, even if a discussion on the quality of care and the patient satisfaction cannot be carried on due to lack of the related data, it is worthwhile noting that a long WT could possibly lead to compromising the quality of care. On the other hand, from a service quality point of view, certainly WT significantly affects patient satisfaction.

As concerns the total time TT, even if it does not coincide with LOS (since the initial part of the pathway until the end of the triage is not considered), it represents the most significant component of ED throughput, thus being mostly responsible for the ED crowding.

\subsection*{5.1. Input analysis}

Input analysis is based on real data concerning the ED collected during February 2018, as reported in Section 4. The data were used for a detailed input analysis of all the
processes in the ED, namely the patient arrival process and the processes related to visits and additional examinations and reassessments.

Patient arrival process to an ED has been widely studied in the literature. A proper nonstationary process must be considered to reproduce such time-dependent arrival process, and the standard assumption adopted is that the arrival process to an ED can be modeled as a nonhomogeneous Poisson process (NHPP). In fact, as well known, NHPP has nonstationary increments, and this makes the use of NHPP suitable for modeling patient arrival process, which is usually strongly time-varying. Then, statistical tests are applied to data to check that NHPP hypothesis holds. This is typically performed by assuming that NHPP has an approximately piecewise constant rate.

In our case study, to obtain a good accuracy of the arrival rate, and following the usual approach proposed in literature, we consider 24 time slots for each day at an hourly basis, starting from 00:00. A plot of the hourly arrival rate for each day of the week obtained from the collected data is reported in Figure 3. It shows a within-day and day-to-day variation in the number of arrivals. In particular, the maximum value of the hourly arrival rate is attained on Monday, while Sunday is the day with the least number of arrivals. Moreover, a slight increasing trend in the daily arrivals peak is observed from Tuesday to Saturday. We used the Kolmogorov–Smirnov statistical test applied to each 1-h interval as a goodness of fit test. Note that, recently, a more sophisticated technique which considers not equally spaced intervals has been proposed in the paper by De Santis, Giovannelli, Lucidi, Messedaglia, Roma, but we have not considered it here. On the basis of these considerations, we estimate the arrival rate on hourly basis and by distinguishing among the different days of the week.

As regards the timing employed in the visit process and in the additional examinations and reassessments process, we used the collected data to obtain the probability distribution of such times. To this aim, we used standard statistical procedure (see, e.g., Chapter 6 of the book by Law). Namely, based on summary statistics and histograms of the real data, we first hypothesized families of distributions that might be representative, and then, we performed parameter estimation. Finally, we used the Kolmogorov–Smirnov goodness of fit test for assessing whether the data are a sample of the particular probability distribution hypothesized. The obtained probability distribution of visit times and additional examinations and reassessments times (in minutes) are reported in Table 7 for each color tag.

5.2. Model verification and validation
To guarantee that the DES model we built provide us with sufficient accuracy of the output, the model has been widely verified and validated by using standard techniques. In particular, after a preliminary debugging, we ran the simulation model under several different settings of the input parameters, accurately checking its functioning and observing the output of each run, to determine whether all the logical paths have been correctly implemented. Model trace has been also used for a deepened verification of the model.

As regards the model validation, we compared the real system values with the corresponding simulation outputs, namely the average values (with their confidence interval) obtained from 50 independent simulation replications, each of them 35 days long, with a warm up period of 7 days. In this way, we can perform a fair comparison with data which refer to 28 days of February. In particular,
we consider some fundamental KPIs of the overall process in terms of time and entity counters.

As concerns KPIs related to process times, we focus on the waiting time WT and on the total time TT previously defined. In Figures 4 and 5, we report the current values, namely those corresponding to the “as-is” status, and the simulation output of WT and TT (in minutes) with the relative confidence interval (with 95% confidence level).

These plots evidence that the simulation output is a good approximation of the real system values since for each color tag, the current values are either within the corresponding confidence interval or close to it.

As regards the entity counters, we compare the current values of the outcomes as reported in Table 6 with the corresponding outputs of the simulation model reported in Table 8 (for the sake of brevity, we do not report the corresponding plots). A comparison between the two tables clearly evidences that the simulation model shows a good accuracy in representing such average values. In fact, the model output values corresponding to each outcome and to each color tag are an accurate approximation of the current values, taking into account the confidence interval.

The previous paragraphs evidence that our simulation model provides an accurate representation of the actual system. As last step needed to validate the model, we showed the obtained results to ED personnel, acquiring important feedback and assessments.

6. Design of experiments and results

In this section, we report experimental results obtained by our DES model. Our aim is to determine performance measures of the ED, to evaluate the impact on the ED of patient peak arrivals due to a critical event. To this aim, we consider hypothetical scenarios where patient arrival rate is artificially changed. In particular, we preliminarily consider an increase of a prefixed percentage of the arrival rate due to the growth in demand. Then, we analyze a mildly loaded situation, namely a gradual increase of patient arrivals over a period of few days of the week. Finally, we turn to the main focus of this work, namely extremely loaded situations, possibly due to some critical conditions, for instance, a natural disaster.

In our implementation, we use an ARENA built-in tool8 to generate entity arrivals according to a nonstationary Poisson process with a varying rate, so that we can easily modify the arrival rates corresponding to different scenarios.

It is important to highlight that in our experimentation, we adopt the standard assumption that the service rate of

| Table 8. Output values (with confidence interval) for the outcomes returned by the simulation. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | White           | Green           | Yellow          | Red             |
| O1              | 122.08 ± 2.98   | 1023.04 ± 9.49  | 23.82 ± 1.36    |                 |
| O2              | 39.06 ± 1.58    | 499.84 ± 6.61   | 21.56 ± 1.30    |                 |
| O3              | 29.32 ± 1.51    | 184.00 ± 3.93   | 14.58 ± 1.12    |                 |
| O4              |                 | 3.79 ± 0.42     | 3.66 ± 0.52     |                 |
| O5              | 18.72 ± 1.05    | 10.36 ± 0.89    |                 |                 |
| O6              | 3.06 ± 0.55     | 16.36 ± 1.16    | 1.88 ± 0.41     |                 |
| O7              | 6.62 ± 0.82     | 23.44 ± 1.69    | 1.66 ± 0.35     |                 |
| O8              |                 |                 | 1.92 ± 0.39     |                 |
ED personnel is unmodified during the patient peak arrivals. However, recent studies showed that ED physicians and nurses could increase their service rate or adopt some particular strategies in case of increased workload. Some examples are multitasking techniques, early task initiation (where an upstream stage initiates tasks that are usually handled by a downstream stage), and other techniques consisting in adaptive response mechanisms to cope with critical situations emerging when treatments’ requests exceed the normal capacity. Since the service rates are parameters of our model, they could be easily modified. However, we do not consider here an analysis involving service rate increase or the adoption of other adaptive techniques, since we have no information about these possible changes for the ED subject of our study.

In our experimentation, we assess how the ED response changes in each considered scenario. In particular, we consider the KPIs of interest defined in Section 5, i.e., the waiting time WT and the total time TT. Moreover, we monitor the resource utilization focusing on the usage of Area B and Area C. In the literature on ED management under disaster conditions, utilization of ED resources and, in particular, utilization of treatment areas and medical staff are considered among the main indicators for evaluating the impact of a hypothetical critical event and for determining the appropriate resource and staff levels to cope with a disaster scenario. Note that, for an ED under normal conditions and for any general queuing system, the use of such an indicator could be questionable, since there are two conflicting viewpoints: from one side, service managers aim at maximizing the resource utilization (for economical reasons); on the other side, service customers are penalized by such behavior that may cause deterioration of the service quality and possibly long queues. More specifically, in our experimentation, we monitor the resource usage as $(\text{ScheduledTime} - \text{IdleTime})/\text{ScheduledTime}$ computed at each 1-h interval, i.e., the resource usage on hourly basis. We prefer to consider this “continuous” resource utilization measure instead of average usage, since high utilization can cause saturation and performance deterioration, even though usage is low when averaged over a long interval. Data concerning the instantaneous utilization of the resources were collected by using Visual Basic for Applications (VBA) ARENA modules.

![Figure 6. WT (in minutes): comparison between the current “as-is” status (in blue) and a prefixed percentage increase of the arrival rate (in green).](image)

![Figure 7. TT (in minutes): comparison between the current “as-is” status (in blue) and a prefixed percentage increase of the arrival rate (in green).](image)

![Figure 8. Usage of Area B.](image)
6.1. Increase of a prefixed percentage of the arrival rate

We consider an increase of 10% in the hourly arrival rate with respect to the current value. We run 50 independent replications, and the length of each replication is 35 days with a warm up period of 7 days. In Figures 6 and 7, we report the comparison in terms of WT and TT, respectively. Of course, the uniform increase in the demand implies longer waiting/stay times. However, this growth in the arrival rate does not significantly affect waiting/stay times for yellow and red tagged patients. This is mainly due to the priority criterion and also to the small number of red and yellow tagged patients with respect to the green and white ones. In Figures 8 and 9, we report the comparison between the usage of Area B and Area C over the 24 h. For the sake of clarity of the plots, in the figures, we report usage based on 3-h time slots. In this scenario analysis, we do not consider the usage of Area A because of the reduced number of red tagged patients. Figure 8 shows the usage of Area B in the rush hours is close to one even in the “as-is” status and that the percentage increase causes a corresponding uniform growing of the utilization, as expected. Before discussing the usage of Area C, note that during the night, only Area B is used, specifically for the treatment of both green and yellow tagged patients, since only one physician is on duty. Therefore, as shown in Figure 9, no patient is visited in Area C during the night. Conversely, this area is strongly used throughout the day when two physicians are on duty, giving rise to a uniform increase in the usage, according to the growth in the average hourly arrival rate.

6.2. A mildly and an extremely loaded scenario

Now we consider unexpected conditions due to a spike in the patient arrival rate related to a sudden and critical event (for instance, in the extreme case, an earthquake). We focus on two possible artificial scenarios, namely both a mildly and an extremely loaded scenario corresponding to two different unpredictable occurrences. It is important to note that in this case, a terminating simulation must be used since we are interested in monitoring the actual effect of arrival spikes on the ED as an unsteady system. The aim is to avoid that too many occurrences concerning standard days (without spikes) are included in the statistical analysis. This would occur if the KPIs were computed by averaging over a long run, e.g., 35 days. Therefore, we chose 2 weeks as replication length and a warm up period of 7 days to avoid bias due to initial conditions (empty system). In this manner, the statistical analysis is focused on the week containing the peak arrivals and concentrated on the related transient state. For each experiment, we run 50 independent replications.

As regards the mildly loaded situation, we adopt a gradual increase/decrease in the arrival rate over the first 3 days of the week. More precisely, similarly to Ahalt et al., we increase the arrival rate from 5% to 25%, depending on time slots, according to the scheme in Table 9. As concerns the extremely loaded scenario, we try to reproduce a major emergency. To this aim, we consider a 300% increase in the arrival rate centered over the 24 h of Monday.

Figure 10 reports the increased hourly arrival rate for both scenarios along with the unmodified arrival rate. In Figures 11 and 12, we report the comparison between the current “as-is” status and the two scenarios in terms of WT. Similarly, in Figure 13, the same comparison is reported in terms of TT. As expected, in the extremely

![Figure 9. Usage of Area C.](image_url)}
In this case, even a huge increase in the overall number of arrivals does not lead to exceed one red tagged patient arrival per hour. Therefore, both WT and TT do not grow significantly, also due to the high priority assigned to these patients. A similar result is observed for the yellow tagged patients. Moreover, note that the WT for red tagged patients is still approximately zero, in accordance with their high urgency level.

Figures 14 and 15 report the comparison between the current “as-is” status and the two artificial scenarios in

**Figure 10.** Increased patient arrival rate (mildly loaded in gray, extremely loaded in yellow) and the unmodified arrival rate (in blue).

**Figure 11.** WT (in minutes): comparison between the current “as-is” status (in blue) and the mildly (in gray) and extremely (in yellow) loaded scenarios.

**Figure 12.** WT (in minutes): detail for yellow and red tagged patients of the comparison reported in Figure 11.

**Figure 13.** TT (in minutes): comparison between the current “as-is” status (in blue) and the mildly (in gray) and extremely (in yellow) loaded scenarios.
terms of Area B and Area C usage. For the sake of clarity of the plots, in the figures, we report usage based on 3-h time slots (Note that in these figures and those reported in the sequel, in a few cases, the confidence interval bars cannot be well represented, since their length is very small). From both these figures, it can be observed how, in the two scenarios, the peak in the patient arrivals causes a sudden increase in the usage of both the resources (Area B and Area C). In the case of extremely loaded scenario, the peak causes resource saturation even immediately before and after the peak center. Note how this phenomenon can be observed only by monitoring the instantaneous resource usage rather than the average utilization.

Now we analyze more in detail the extremely loaded scenario. Indeed, due to the unpredictability of the phenomenon of peak arrivals caused by critical events, it is difficult to create artificial scenarios that actually reproduce what could happen in the real system. Therefore, we now analyze some variants of the 300% increase in the arrival rate already considered. In particular, we report the comparison of the current “as-is” status with respect to increases of 100%, 200%, and 400% in the arrival rate (always centered over the 24 h of Monday and with the same percentage distribution of the color tags). In Figures 16–18, the corresponding WT and the TT are reported, along with those obtained for the 300% increase scenario. From Figure 17, it can be observed how WT for the red tagged patients still remains acceptable for all the four scenarios, and this is due to the low percentage of red tagged patient arrivals. As regards the yellow tagged ones, WT remains below 1 h only for the 100% increase. As concerns the white and green tagged patients, WT becomes unacceptable even with the 100% increase. The TT reported in Figure 18 is a direct consequence of the corresponding WT.

The same comparison between the current “as-is” status and the increases of 100%, 200%, and 400% in the arrival rate is reported in Figures 19 and 20 in terms of resource usage for Area B and Area C, respectively. Also in this case, we report plots based on 3-h time slots. These figures clearly highlight how, as expected, the percentage increase in the patient arrival rate strongly affects the utilization of both the visit areas. Note that the usage of Area B also depends on the yellow tagged patients that are visited in this area during the night, when Area C is not
Both resources reach saturation points even in the most cautious scenario (100% increase).

All the scenarios up to now analyzed are based on increases in the patient arrival rate, keeping unchanged the percentage distribution of different color tagged patients. Actually, during a critical event, it is also likely to assume that the percentage of high priority patients grows during the arrival rate peak. During the latest earthquake (24 August 2016) that hit Central Italian regions (where the ED considered in this work is located), up to 14 patients with trauma due to crushing (i.e., red tagged patients) requested assistance in the hour corresponding to the peak in the arrivals. As already mentioned in Section 3, in these cases, i.e., in case of the so called “maxi-emergency,” Italian EDs adopt the “Internal Emergency Plan for Massive Inflow of Injured” (we use the Italian acronym PEIMAF), according to the current regulation. This implies the availability of additional resources and the adoption of different operating rules aimed at providing an adequate and timely assistance to all the patients who require it. Of course, although such a plan cannot be tested during the normal ED activity, an accurate assessment of its effectiveness must be performed in advance in view of its potential activation. A natural way for performing such a testing is to adopt a DES model. Therefore, we used our DES model also to provide the decision makers with useful insights concerning the design of the PEIMAF.

In the sequel, we report some analyses aiming at reproducing a critical situation corresponding to the extremely loaded scenario with an increase in the arrival rate and, in addition, an increase in the red tagged patient arrivals. In particular, we assume both an increase of 400% in the arrival rate and an increase in the percentage of red tagged

![Figure 16. WT (in minutes): comparison between the current "as-is" status (in gray) and the extremely loaded scenario with increases in the arrival rate of 100% (in blue), 200% (in orange), 300% (in yellow), and 400% (in light blue).](image1)

![Figure 17. WT (in minutes): detail for yellow and red tagged patients of the comparison reported in Figure 16.](image2)

![Figure 18. TT (in minutes): comparison between the current "as-is" status (in gray) and the extremely loaded scenario with increases in the arrival rate of 100% (in blue), 200% (in orange), 300% (in yellow), and 400% (in light blue).](image3)

![Figure 19. Usage of Area B: the current “as-is” status and the extremely loaded scenarios.](image4)
patient arrivals, to obtain about 14 of these patients arriving during the peak hour, as really occurred during the recent earthquake. Moreover, we assume to adopt a possible maxi-emergency PEIMAF plan and to assess its effectiveness through the comparison of the KPIs obtained. More specifically, we adopt the following assumptions:

**A1 Patient arrivals:**
The percentage of color tags assigned at the triage station is modified during the whole peak day, by assuming that 35% of the arrivals are red tagged patients.

**A2 Maxi-emergency plan (PEIMAF):**
The number of physicians and nurses on duty is doubled during the peak day, starting from the peak hour (10:00 a.m.) and then the shifts return to the normal scheme; Green and white tagged patients are not admitted to the ED, starting from the peak hour (10:00 a.m.), but they are sent to outpatient facilities; Also Area B and Area C can be used for the treatment of red tagged patients.

In this manner, by A1, we obtain about 14 red tagged patient arrivals during the peak hour, trying to reproduce a really occurred critical situation. By A2, we implement a possible simple configuration of a maxi-emergency plan, only for experimental purposes. Actually, the operational procedures provided by a PEIMAF plan are much more complex and articulate than the ones reported in this paper: here we consider only an illustrative example to show how our DES model can be fruitfully used to test a maxi-emergency plan.

Figures 21 and 22 report the WT and the TT for the “as-is” status and the extremely loaded scenario with the modified percentage of red tags assigned at the triage as in A1, with (in yellow) and without (in gray) adopting a maxi-emergency plan as in A2.
tagged patients and 1 h for the red tagged ones and, obviously, this is unacceptable. This situation is confirmed by the plot of the usage of the visit areas, reported in Figures 23–25. First, note that when the emergency plan is not activated, since only two physicians are on duty during the peak day, they both remain assigned to *Area A* throughout the day. This is due to the large number of red patients to be visited in this area. Since there are no physicians assigned to *Area B* and *Area C*, the usage level of these areas is zero until the distribution percentage of the red patients returns to the normal scheme. On the contrary, when the emergency plan is activated, since four

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**Figure 23.** Usage of *Area A*: the current “as-is” status and the extremely loaded scenario with and without the maxi-emergency plan.

**Figure 24.** Usage of *Area B*: the current “as-is” status and the extremely loaded scenario with and without the maxi-emergency plan.

**Figure 25.** Usage of *Area C*: the current “as-is” status and the extremely loaded scenario with and without the maxi-emergency plan.
physicians are on duty during the peak day, even Area B and Area C can be used for the treatment of higher complexity patients. As a consequence, all the visit areas are used. After the peak arrivals end, the utilization of Area B and Area C decreases since the extra human resources allow more patients to be visited at the same time, whereas the utilization of Area A drops to zero. In any case, even if the adoption of the maxi-emergency plan as assumed in A2 leads to an improvement, its overall inadequacy is very evident. The resource saturation is reached for long periods, implying that the resources would have extra requests which cannot be satisfied and, hence, they would be queued. To cope with this situation, an enlargement of the resources, whether human or physical, would be desirable even if not sufficient in most cases. Emergency plans usually provide for an increase of ED personnel, while an extension of physical rooms (even if temporary) is usually more difficult. Of course, patient diversion policy toward neighboring EDs should be adopted in case of an excessive ED congestion. As regards explicit suggestions about a design of a new emergency plan based on the scenario analysis reported in our paper, we are still in touch with the ED staff, aiming at using our model to evaluate possible novel proposals. In fact, any proposal for changes in the ED functioning must be first validated from a medical/clinical viewpoint. We believe that being aware in advance of the real operational capacity of an ED in case of peak arrivals could be really important for the ED managers. Indeed, this would allow them to design or adjust a maxi-emergency plan, taking into account the specific environmental context as well. Thanks to the high flexibility of our ARENA implementation of the DES model concerning the ED under study, an extensive scenario analysis can be performed assessing the ED operational capacity, namely all the KPIs of interest in many and different real critical situations.

7. Conclusion

In this paper, we propose a DES model for studying the ED of a medium-size hospital in a region of Center Italy recently hit by a severe earthquake. The aim is to assess how fundamental KPIs change in response to different increase patterns of the patient arrival rate. In particular, we focus on critical events, like a natural disaster, which could lead to extremely loaded situations. To evaluate the performance of the ED under study, we consider time-related measurements as well as resource usage. Several scenarios have been considered, including the ones artificially created, trying to reproduce real mass casualty occurrences. The experimental results showed that, when the increase of the arrival rate is low or moderate, the ED performance does not significantly deteriorate. Instead, in case of extreme events with high patient peak arrivals, the adoption of an exceptional emergency plan is necessary to ensure effective and timely assistance.

The model proposed in this paper refers to a specific case study, but thanks to the flexibility of its implementation, it can be easily adapted to reproduce the patient flow of other EDs. We believe that the model we proposed has a twofold merit: it represents an effective decision support system; indeed, it enables decision makers to assess the performance of the ED under study and to better allocate ED resources. Moreover, the model can be used to perform scenario analyses to help managers to define in advance maxi-emergency plans which, of course, cannot be tested during the normal activity of the ED.

On the other hand, this study clearly presents some practical limitations. First, the patient arrivals in the different scenarios are generated by using the same probability distribution with changed mean. This is an assumption commonly adopted, due to a lack of data on specific arrival patterns during critical events. Furthermore, it was not possible to assess how the quality of care and the patient satisfaction change by adopting different ED settings. Even the number of LWBS patients cannot be considered to this aim when PEIMAF is adopted. Indeed, in this latter case, green and yellow tagged patients are not admitted to the ED, but sent to outpatient facilities. Of course, the remaining red tagged patients and usually also the yellow tagged ones do not leave without being treated. However, we believe that this is not a major limitation for the scope of this study.

As future work, when further suited information is available, we could easily include it in our model, allowing us to overcome the existing limitations. Moreover, we can also consider further components, like fast track or see and treat pathways, as well as changes of physician and nurse service rate.

Acknowledgements

The authors wish to express their gratitude to Dr. Stefania Mancinelli and to Dr. Marco Pierandrei from “Direzione Medica Ospedale di Fabriano” who enabled them to carry out this study. Moreover they thank Dr. Massimo Maurici and Ing. Luca Paulon from “Dipartimento di Biomedicina e Prevenzione” and “Laboratorio di Simulazione e Ottimizzazione dei servizi del SSN” of the Università di Roma “Tor Vergata,” for useful discussions on an early stage of this work. The authors wish to thank the anonymous reviewers for their constructive comments and suggestions which led to improve the paper.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
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References
1. Aringhieri R, Bruni M, Khodaparasti S, et al. Emergency medical services and beyond: addressing new challenges through a wide literature review. Comput Oper Res 2017; 78: 349–368.
2. Hoot N and Aronsky D. Systematic review of emergency department crowding: causes, effects, and solutions. Ann Emerg Med 2008; 52: 126–136.
3. Weiss S, Derlet R, Amdahl J, et al. Estimating the degree of emergency department overcrowding in academic medical centers: results of the National Ed Overcrowding Study (NEDOCS). Acad Emerg Med 2004; 11: 38–50.
4. Weiss S, Ernst AA and Nick TG. Comparison of the national emergency department overcrowding scale and the emergency department work index for quantifying emergency department crowding. Acad Emerg Med 2006; 13: 513–518.
5. Chan C, Green L, Lekwijit S, et al. Assessing the impact of service level when customer needs are uncertain: an empirical investigation of hospital step-down units. Manage Sci 2019; 65: 751–775.
6. Hasan I, Bahalke E and Yih Y. Evaluating intensive care unit admission and discharge policies using a discrete event simulation model. Simulation 2020; 96: 501–518.
7. Rockwell-Software. Arena user’s guide. Milwaukee, WI: Rockwell Automation, 2010.
8. Kelton W, Sadowski R and Zupick N. Simulation with arena. 6th ed. New York: McGraw-Hill Professional, 2014.
9. Reid P, Compton W, Grossman J, et al. Building a better delivery system: a new engineering/health care partnership. Washington, DC: The National Academies of Press, 2005.
10. Almagooshi S. Simulation modelling in healthcare: challenges and trends. Procedia Manuf 2015; 3: 301–307.
11. Aboueljineane L, Sahin E and Jemai Z. A review on simulation models applied to emergency medical service operations. Comput Ind Eng 2013; 66: 734–750.
12. Bedoya-Valencia L and Kirac E. Evaluating alternative resource allocation in an emergency department using discrete event simulation. Simulation 2016; 92: 1041–1051.
13. Gul M and Guneru AF. A comprehensive review of emergency department simulation applications for normal and disaster conditions. Comput Ind Eng 2015; 83: 327–344.
14. Joshi V, Lim C and Teng SG. Simulation study: improvement for non-urgent patient processes in the emergency department. Eng Manag J 2016; 28: 3145–3157.
15. Kuo Y, Rado O, Lupia B, et al. Improving the efficiency of a hospital emergency department: a simulation study with indirectly imputed service-time distributions. Flex Serv Manuf J 2016; 28: 120–147.
16. Rado O, Lupia B, Leung JM, et al. Using simulation to analyze patient flows in a hospital emergency department in Hong Kong. In: Matta A, Li J, Sahin E, et al. (eds) Proceedings of the international conference on health care systems engineering. Cham: Springer International Publishing, pp. 289–301.
17. Wong ZSY, Lit ACH, Leung SY, et al. A discrete-event simulation study for emergency room capacity management in a Hong Kong Hospital. In: 2016 winter simulation conference (WSC), Washington, DC, 11–14 December 2016, pp. 1970–1981. New York: IEEE.
18. Zeinali F, Mahootchi M and Sepehri M. Resource planning in the emergency departments: a simulation-base metamodeling approach. Simul Model Pract Th 2015; 53: 123–138.
19. Aringhieri R, Bonetta G and Duma D. Reducing overcrowding at the emergency department through a different physician and nurse shift organisation: a case study. In: Daniele P and Serimali L (eds) New trends in emergency complex real life problems. AIO Springer Series, vol. 1. Cham: Springer Nature, pp. 43–53.
20. Kaushal A, Zhao Y, Peng Q, et al. Evaluation of fast track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department. Socio Econ Plan Sci 2015; 50: 18–31.
21. Liu Z, Cabrera E, Taboada M, et al. Quantitative evaluation of decision effects in the management of emergency department problems. Procedia Comput Sci 2015; 51: 433–442.
22. Taboada M, Cabrera E, Iglesias ML, et al. An agent-based decision support system for hospitals emergency departments. Procedia Comput Sci 2011; 4: 1870–1879.
23. Wang L. An agent-based simulation for workflow in emergency department. In: 2009 Systems and information engineering design symposium, Charlottesville, VA, 24 April 2009, pp. 19–23. New York: IEEE.
24. Paul SA, Reddy MC and De Flitch CJ. A systematic review of simulation studies investigating emergency department overcrowding. Simulation 2010; 86: 559–571.
25. Nahhas A, Alwadi A and Reggelin T. Simulation and the emergency department overcrowding problem. Procedia Engineer 2017; 178: 368–376.
26. Kuo YH, Leung JM, Graham CA, et al. Using simulation to assess the impacts of the adoption of a fast-track system for hospital emergency services. J Adv Mech Des Syst 2018; 12: 1–11.
27. Aroua A and Abdulnour G. Optimization of the emergency department in hospitals using simulation and experimental design: case study. In: 2017 Winter simulation conference (WSC), Las Vegas, NV, 3–6 December 2017, pp. 4511–4513. New York: IEEE.
28. Whitt W and Zhang X. A data-driven model of an emergency department. Oper Res Health Care 2017; 12: 1–15.
29. Daldoul D, Nouaouri I, Bouchriha H, et al. A stochastic model to minimize patient waiting time in an emergency department. Oper Res Health Care 2018; 18: 16–25.
30. Ahsan K, Alam M, Morel D, et al. Emergency department resource optimisation for improved performance: a review. J Ind Eng Int 2019; 15: S253–S266.
31. Chanchaichujit J, Tan A, Meng F, et al. Optimization, simulation and predictive analytics in healthcare. London: Palgrave Pivot, 2019, pp. 95–121.
32. Granja C, Almada-Lobo B, Janela F, et al. An optimization based on simulation approach to the patient admission scheduling problem using a linear programing algorithm. J Biomed Inform 2014; 52: 427–437.
33. Lucidi S, Maurici M, Paulon L, et al. A derivative-free approach for a simulation-based optimization problem in healthcare. *Optim Lett* 2016; 10: 219–235.
34. Lucidi S, Maurici M, Paulon L, et al. A simulation-based multiobjective optimization approach for health care service management. *IEEE T Autom Sci Eng* 2016; 13: 1480–1491.
35. Zhang H, Best T, Chivu A, et al. Simulation-based optimization to improve hospital patient assignment to physicians and clinical units. *Health Care Manag Sci* 2020; 23: 117–141.
36. Yousefi M, Yousefi M and Fogliatto F. Simulation-based optimization methods applied in hospital emergency departments: a systematic review. *Simulation* 2020; 96: 791–806.
37. Ahmed MA and Alkhamis TM. Simulation optimization for an emergency department healthcare unit in Kuwait. *Eur J Oper Res* 2009; 198: 936–942.
38. Diefenbach M and Kozan E. Effects of bed configurations at a hospital emergency department. *J Simul* 2011; 5: 44–57.
39. Guo H, Gao S, Tsui K, et al. Simulation optimization for medical staff configuration at emergency department in Hong Kong. *IEEE T Autom Sci Eng* 2017; 14: 1655–1665.
40. Guo H, Goldsman D, Tsui KL, et al. Using simulation and optimisation to characterise durations of emergency department service times with incomplete data. *Int J Prod Res* 2016; 54: 6494–6511.
41. Kadri F, Chaabane S and Tahonauthore C. A simulation-based decision support system to predict and prevent strain situations in emergency department systems. *Simul Model Pract Th* 2014; 32: 42–52.
42. Xia N, Sharman R, Rao H, et al. A simulation-based study for managing hospital emergency department’s capacity in extreme events. *Int J Bus Excel* 2012; 5: 140–154.
43. Patvivatsiri L. A simulation model for bioterrorism preparedness in an emergency room. In: *Proceedings of the 2006 winter simulation conference* (ed Perrone L, Wieland FP, Liu J, et al.), Monterey, CA, 3–6 December 2006, pp. 501–508. New York: IEEE.
44. Al-Kattan I and Abboud B. Disaster recovery plan development for the emergency department—case study. *Public Admin Manag* 2009; 13: 75–99.
45. Joshi A and Rys M. Study on the effect of different arrival patterns on an emergency department’s capacity using discrete event simulation. *Int J Ind Eng* 2011; 18: 40–50.
46. Cao H and Huang S. Principles of scarce medical resource allocation in natural disaster relief: a simulation approach. *Med Decis Making* 2012; 32: 470–476.
47. Gul M and Guneri A. Simulation modelling of a patient surge in an emergency department under disaster conditions. *Croat Oper Res Rev* 2015; 6: 429–443.
48. Gul M, Guneri A and Gunal M. Emergency department network under disaster conditions: the case of possible major Istanbul earthquake. *J Oper Res Soc* 2020; 71: 733–747.
49. Ministero della Salute. *Documento di proposta di aggiornamento delle linee guida sul triage intraospedaliero*. G.U. Serie Generale, n. 285, 7 dicembre 2001.
50. Presidenza del Consiglio dei Ministri. *Accordo Stato Regioni, Riorganizzazione del sistema di emergenza urgenza in rapporto alla continuità assistenziale*. Rep. Atti n.36/CSR, 2013.

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