Challenges of Trustable AI and Added-Value on Health
B. Séroussi et al. (Eds.)

doi:10.3233/SHTI220402

Analysis of Saturation in the Emergency Department: A Data-Driven Queuing Model Using Machine Learning

Adrien WARTELLE[a,b,1], Farah MOURAD-CHEHADE[b], Farouk YALAOUI[b], David LAPLANCHE[b] and Stéphane SANCHEZ[b,c]
[a] *Computer Science and Digital Society Laboratory (LIST3N), Université de Technologie de Troyes, Troyes, France (e-mail: adrien.wartelle@utt.fr, farah.chehade@utt.fr, farouk.yalaoui@utt.fr)*
[b] *Public Health and Performance Department, Centre Hospitalier de Troyes, Troyes, France (e-mail: david.laplache@hcs-sante.fr, stephane.sanchez@hcs-sante.fr,*
[c] *Research on Health University Department – University of Reims Champagne Ardenne, Reims, France*

Abstract. Emergency department is a key component of the health system where the management of crowding situations is crucial to the well-being of patients. This study proposes a new machine learning methodology and a queuing network model to measure and optimize crowding through a congestion indicator, which indicates a real-time level saturation.

Keywords. Emergency department, Saturation, Crowding indicator, Queuing model, Data-driven-model, Machine learning-based forecasting model, Simulation-Optimization.

1. Introduction

Emergency department (ED) is a key component of the health system that acts as a safety net of healthcare for the population around. With its unscheduled nature and its ease to be accessed, it is subject to real-time crowding phenomena with serious consequences on patients' health and on doctor and nurses working conditions (1). Its causes have been related to the input of ED, that is patient arrivals volumes, the throughput with examination services time performances and output with downstream blocking of patients due to shortage of hospitalization beds.

ED crowding is a complex problem not only regarding its causes but also regarding its definition and the way it is quantified as illustrate the many ED crowding scores existing in the literature such as the EWIN, READI, SONET and NEDOCS (2,3). They each try to quantify the stress that patients' healthcare demand put on the ED system in comparison to the availability of resources. Especially, the National Emergency Department Overcrowding Score (NEDOCS) has been designed to correlate the most with the empirical real-time evaluation of ED crowdedness by field experts using a linear regression on 5 key variables (4). However, all these scores do not necessarily better than

[1] Corresponding Author, Adrien WARTELLE; E-mail: adrien.wartelle@utt.fr.

global mean occupation to predict consequences of crowding and the variables they use are not always available in data records (3,5). As such, crowding can be seen mainly as an occupation level problem which is in turn a direct consequence of saturation periods where the rate of patient arrivals is greater than the rate of departures.

Queuing networks models are well suited to model these crowding events as they can capture all these metrics. Their design differs mainly on four criterions which are their granularity, the queuing mechanisms with the type of servers involved, the type of variables modeled to characterize the service processes and the technique of estimation for arrivals and services time or rate variables. The model granularity is linked to the number of stations and patient pathways and can go from one station model (6) to complex detailed models with the distinction of each action and processes (2,7,8). The servers of the stations can represent resources such as beds, nurses, and doctors (8), or be more abstract with a single server or infinite servers (6,9). The services processes can also be seen either as a succession of services times (2,7,8) or as a point process with a variable intensity of service rate (6,9). Their end goal is either to predict future crowding values using data-driven approach (3,6), or to optimize crowding with theoretical model which takes into account the effect of decision variables such as staff planning (8). However, no model exists yet to both forecast and optimize crowding at the same time which could provide better and more robust planification and decision-making strategies that could in-turn be adapted given the crowding context and the time scale considered.

The aim of this study was to propose a new methodology perspective on crowding measurement, forecasting and optimization using data-driven queuing approach as well as an original congestion indicator to measure saturation.

2. Methods

2.1. Design and Definition of congestion

We conduct a large retrospective observational study based on emergency department record during 2017 to 2019. Emergency department is a service system which can be captured by a mathematical model on a discrete space with continuous time using an arrival process $A(t)$ and a departure process $D(t)$ which describe, respectively, the number of arrivals and departures of the system since an initial period $t = 0$. Instead of focusing only on the occupation level $l(t) = A(t) - D(t)$, the present study focuses on an original congestion measure:

$$\rho(t) = \frac{f(A(t) - A(t-h))}{g(D(t) - D(t-h))} \quad \forall t \in \mathbb{R}^+, t > h \quad (1)$$

The congestion $\rho(t)$ uses a ratio comparison of arrivals to departures on a time window $[t - h, t]$ and with regulating functions $f(.)$ and $g(.)$ which are both chosen to ensure a local and stable indicator where $\rho(t) > 1$ indicates local system saturation.

2.2. Queuing methodology

To model this new indicator, the stochastic arrival and departure processes $A(t)$ and $D(t)$ need to be fully modelized. To achieve this goal, this study proposes an ED queuing network using a set of elementary stations $i \in I$, with their arrivals $A_i(t)$ and departures

$D_i(t)$ processes, including an external environment indexed by 0 and set of stations $F \in \mathcal{F} \subset \mathcal{P}(I)$. For practical purpose, a discretization of space is introduced with $A([t, t+k]) = A(t+k) - A(t)$ (same for D) and $k \in \mathbb{R}^+$ the length of time interval unit. The arrival processes of each station are connected to the departure of others with transition processes D_{i_1,i_2} , $i_1, i_2 \in I$ and governed by the transition probabilities $p_{i_1,i_2}([t, t+k])$. As illustrated in Figure 1, the considered queuing network is a 7 station ED patient flow model with 2 tracks, a short circuit for patients with low-acuity health problems and a long circuit for the others. The patients follow a classic ED process of nurse triage, doctor initial examination, supplementary examinations and a holding before leaving the ED for home or hospitalization in most cases.

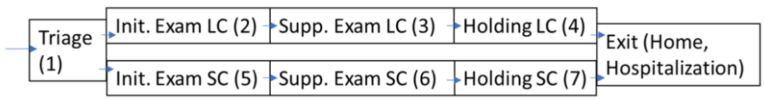

Figure 1. General ED Patient Flow model (LC: Long Circuit, SC: Short Circuit)

The final goal of the queuing approach is to model the distributions $P(A_F([t, t+k] = n), P(D_F([t, t+k] = n), \forall n \in \mathbb{N}, \forall F \in \mathcal{F}, \forall t \in \{t = nk, n \in \mathbb{N}\}$. The proposed modelization considers each of the 7 departure processes of the ED queuing network as Coxian processes described by a local departure rate function whose behavior is inferred using past information on service performances and current information about the number of patients in the ED and the number of triage nurses and doctors in long and short circuits (10). The obtained queuing model can then be simulated evaluate, forecast, and optimize crowding using notably the original congestion measure. This study was performed in compliance with the national legislation regarding epidemiological studies (Declaration N° 2203674v0). Since the study was wholly observational and only used anonymized data (patient names were not recorded), neither ethics approval nor a specific written informed consent from participants were required under French law as a retrospective database study.

3. Results

The data involved for the evaluation of the method come from the ED of Troyes Hospital in Eastern France during the year 2017 to 2019 with a focus on 2019. It is the largest hospital in the Aube Department of France which has a population of 310,000 inhabitants and a medical density of 234.1 physicians per 100,000 inhabitants. In 2018, there were a total of 62,082 ED visits corresponding to an average use rate of 250 to 330 visits per 1,000 inhabitants within the hospital's service area.

3.1. Congestion characteristic of the ED of Troyes

For each 4-hour period of the day of 2019, the Table 1 describes key crowding metrics with the mean 2h-lag number of arrivals (A), the mean 2h-lag number of departures (D), the mean occupation level (L) and the mean 2h-lag congestion ($\bar{\rho}$) (h=2). To keep a stable finite congestion, the regulation functions add one arrival and one departure event.

Table 1. Key ED crowding metrics for Troyes ED in 2019

Hour period	0h-4h	4h-8h	8h-12h	12h-16h	16h-20h	20h-24h	0h-24h
L	40.7	24.4	16.2	26.7	42.7	45.4	32.7
$\bar{\rho}$ (~A/D)	0.9 (~17.2/21.3)	0.6 (~9.0/17.1)	0.9 (~5.4/7.8)	2.4 (~16.0/7.9)	1.6 (~21.8/15.0)	1.0 (~21.0/21.3)	1.2 (~15.1/15.1)

3.2. Queuing model parameters and validity

The first and most important step of the queuing network development which is to model the departure process of each station has been undertaken. The departures rates are currently modeled using logistic regression on the probability of at least one departure on 1 second intervals which is taken as a polynomial function of the variables described in the method section. Figures 2 and 3 show the estimated departures rates per hour of the model for the initial examination stations (EXAMCLI for long circuit and EXAMCCI for short circuit) for short circuit depending on the current number of medical actors (LM) and patients (LP) present.

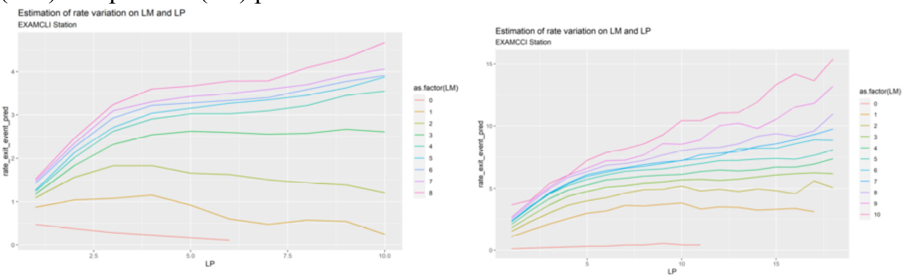

Figure 2 and 3. Estimated rates of departures

Although the forecasting performances of congestion have not yet been evaluated, the models have been checked for the adequation between mean occupation level observed over the year 2019 (L) and the one produced by simulation ($\hat{L}$) of each station independently considering their arrival process as known using the mean of 10 simulation replications.

Table 2. Simulation of ED Troyes 2019 crowding occupation, bias fit

Station	T (1)	I.E LC (2)	S.E LC (3)	H LC (4)	I.E SC (5)	S.E SC (6)	H SC (7)	Sum
Bias: $\hat{L}$ -L	3.3-3 = 0,3 (11.4%)	4.4-4.1=0,3 (8.7%)	11.2-11.2=0 (0.7%)	2.3-2.3=0 (-1.5%)	5.5-5 = 0.5 (9.6%)	5.6-5.7 =0.1 (-1.2%)	1.7-1.5 = 0.2 (14.0%)	34-32.7 = 1.3 (3.7%)

4. Discussion and Conclusion

The queuing model approach for forecasting and optimization of saturation is an original and promising approach. As Table 1 illustrates most of the crowding accumulation ED happens during the beginning of the afternoon (12h-16h) where the mean 2h lag congestion is the highest at 2.4 whereas the peak occupation is attained during the period 20h-24h. The lag of 2 hours has been chosen to give information as local as possible on the saturation as well as to obtain enough events whose mean varies here from 13.2 events (8h-12h) to 42.3 (20h-24h). The results of the queuing models show that they can adequately capture the service performance variations based on the number of patients and of medical actors.

Despite these current promising results, the model still needs to be analyzed further to show its performances to forecast crowding in terms of congestion and occupancy using adequate error metrics and compare them to the literature on forecasting ED occupancy. These forecasting performances are still under encouraging investigation. In the meantime, this study already shows an adequate representation of ED performances and is suitable for simulation-optimization purposes with a 3.7% relative bias error on the total ED occupation, not considering yet the modelization of arrivals in the ED and the transitions models. Furthermore, the queuing design approach can be easily adapted to suit any ED, and even any service system, as long as arrival and departure datetimes are available for forecasting purposes and staff planning or other decision variables can be extracted for optimization. It will form the basis of a management tool to detect future congestion situation in the short and long term and propose solutions toward optimizing it. Staffing planification will form the key strategy of this optimization (11), and will be completed with other complementary strategies. These strategies will consider reorganization of the triage process (12), and the redirection of non-emergent cases (13), toward alternative unscheduled primary care services.

To conclude, our approach explores new methods with current emergency record data to drive healthcare system in real time.

References

[1] Morley C, Unwin M, Peterson GM, Stankovich J, Kinsman L. Emergency department crowding: A systematic review of causes, consequences and solutions. PLoS One [Internet]. 2018;13(8):e0203316.

[2] Ahalt V, Argon NT, Ziya S, Strickler J, Mehrotra A. Comparison of emergency department crowding scores: a discrete-event simulation approach. Health Care Manag Sci. 2018;

[3] Hoot NR, Zhou C, Jones I, Aronsky D. Measuring and Forecasting Emergency Department Crowding in Real Time. Ann Emerg Med [Internet]. 2007 [cited 2021 Jul 2];49(6):747–55.

[4] Weiss SJ, Derlet R, Arndahl J, Ernst AA, Richards J, Fernández-Frankelton M, et al. Estimating the degree of emergency department overcrowding in academic medical centers: results of the National ED Overcrowding Study (NEDOCS). Acad Emerg Med [Internet]. 2004 [cited 2022 Feb 10];11(1):38–50.

[5] Cheng Q, Argon NT, Evans CS, Liu Y, Platts-Mills TF, Ziya S. Forecasting emergency department hourly occupancy using time series analysis. Am J Emerg Med. 2021 Oct 1;48:177–82.

[6] Whitt W, Zhang X. Forecasting arrivals and occupancy levels in an emergency department. Oper Res Heal Care [Internet]. 2019 Jun 1 [cited 2020 Jan 18];21:1–18. Available from: https://www.sciencedirect.com/science/article/abs/pii/S2211692318300407

[7] Bair AE, Song WT, Chen YC, Morris BA. The impact of inpatient boarding on ED efficiency: A discrete-event simulation study. J Med Syst. 2010;

[8] Cochran JK, Roche KT. A multi-class queuing network analysis methodology for improving hospital emergency department performance. Comput Oper Res. 2009;

[9] Sharafat AR, Bayati M. PatientFlowNet: A Deep Learning Approach to Patient Flow Prediction in Emergency Departments. IEEE Access. 2021;9:45552–61.

[10] Vere-Jones, D. J., Daley D. An Introduction to the Theory of Point Processes. An Introduction to the Theory of Point Processes. Springer-Verlag; 2003.

[11] Feng Y-Y, Wu I-C, Chen T-L. Stochastic resource allocation in emergency departments with a multi-objective simulation optimization algorithm. Heal Care Manag Sci 2015 201 [Internet]. 2015 Aug 5 [cited 2021 Oct 18];20(1):55–75. Available from: https://link.springer.com/article/10.1007/s10729-015-9335-1

[12] Chmielewski N, Moretz J. ESI Triage Distribution in U.S. Emergency Departments. Adv Emerg Nurs J [Internet]. 2022 Jan [cited 2022 Jan 31];44(1):46–53. Available from: https://pubmed.ncbi.nlm.nih.gov/35089282/

[13] Tapia AD, Howard JT, Bebo NL, Pfaff JA, Chin EJ, Trueblood WA, et al. A Retrospective Review of Emergency Department Visits That May Be Appropriate for Management in Non-Emergency Settings. Mil Med [Internet]. 2022 Jan 18 [cited 2022 Jan 31]