Original Research Article: full paper

(2024), «EUREKA: Physics and Engineering»
Number 1

DESIGN OF A MODEL FOR IMPROVING EMERGENCY ROOM PERFORMANCE USING A COLORED PETRI NET

Alvaro Jr Caicedo-Rolon✉
Department of Industrial Engineering[1]
alvarojuniorcr@ufps.edu.co

Gustavo Guerrero-Gomez
Department of Mechanical Engineer
Francisco de Paula Santander University Ocana Section
Alcosure road, Ocana, Colombia, 546551

Faustino Moreno-Gamboa
Department of Mechanical Engineer[1]

[1]*Francisco de Paula Santander University*
12 e 96, Gran Colombia ave., Cucuta, Colombia, 54003

✉**Corresponding author**

Abstract

Emergency rooms are one of the most complex and vital areas of healthcare institutions, which have presented overcrowding, long waiting, and length of stay times, affecting the timeliness, responsiveness, and quality of service. This research aimed to design a detailed patient flow model to improve emergency room performance using the hierarchical timed colored Petri nets. Then, the model was simulated to evaluate scenarios considering tactical decisions such as physician staff planning, operational decisions such as adjusting work schedules, and strategic decisions such as increasing observation beds. The best scenario would reduce the average waiting times for triage II patients by 17.30 % and 47.57 %, and triage III by 33.49 % and 43.49 % for medical consultation in the office or the minor surgery room, respectively. In addition, the waiting time in observation and the rate of patients left without being seen by a physician would be reduced by 92.45 % and 74.67 %, respectively. These results improve the quality and timeliness of the service and avoid putting the patient's health and life at risk. The designed model included more attributes for patients concerning the place of medical care in the emergency room, the number of visits to the physician, and the physician who will care for the patient. Moreover, the simulation model includes observation beds as a limited resource blocking new patient admission. Finally, this model is a tool to support emergency room managers in making short, medium, and long-term decisions to address problems such as overcrowding, long waiting and length of stay times, and high rates of patients left without being seen by a physician.

Keywords: healthcare, simulation, decision-making, management, hospital, logistics, emergency, overcrowding, modeling, timeliness.

DOI: 10.21303/2461-4262.2024.002979

1. Introduction

Among the main problems in the emergency room (ER) are overcrowding, long waiting and length of stay (LOS) times, and high rates of patients left without being seen by a physician (LWBS). These issues affect patient satisfaction, quality, and timeliness and put the patient's health and life at risk [1–5].

Waiting time is one of the essential factors in health care management, determining the responsiveness and performance of ER [6–8].

ER waiting times depend on the legislation of the country. For example, the waiting time for triage II patients would vary between 10 and 30 minutes [9–12]. However, this limit is exceeded in some countries because most ERs are overcrowded [1, 2, 5]. This situation has motivated hospital and ER managers to improve operational efficiency and provide better patient service [4, 13–15]. The causes of overcrowding are inefficient operations, limited resources for the growing demand, low availability of observation and hospitalization beds, and budget limitations [6, 16–23].

Moreover, public hospitals have increased demand in Colombia because private clinics do not receive non-critical patients when insurance companies have debts [3].

In this research, a discrete event simulation (DES) model was designed using a colored Petri net (CPN) representing the detailed patient flow of an ER.

Then, the authors simulated the model to evaluate scenarios that improve key performance indicators (KPI), such as patient waiting time for medical consultation, queuing patients in medical consultation, wait time in observation, and LWBS.

In addition, this paper proposed the number of observation beds to prevent patients from being placed on chairs or lying on the floor, avoid patient deviation, and improve the quality of emergency service.

This article presents a model with greater detail than those designed by [1, 2], as it included more attributes (colors) to patients (tokens) concerning the place of medical care in the ER, the number of visits to the physician, and the physician who will care for the patient. This detail allows for measuring and improving more specific indicators, such as waiting times according to the reason for the consultation, which is related to the place of care, such as the physician's office or the minor surgery room. In addition, the simulation model includes observation beds as a limited resource blocking new patient admission and resource utilization, as suggested in a future study by [1, 2], respectively.

Finally, the simulation model is an alternative to support resource planning and ER performance improvement decision-making.

2. Materials and methods

2. 1. A brief description of colored Petri net

According to [24, 25], the DES methodology steps were used. PNs are commonly used for modeling and analyzing discrete event systems [26].

In the PN, places are circles describing processes, queues, geographic location, and resource state.

Transitions are rectangles and model events that occur randomly.

Tokens represented by black dots are in place nodes and model the number of patients in the queue, processes, and available resources.

The arcs (arrows) connect the places and transitions and have an associated weight, which allows describing the necessary conditions for the event represented in the transition to be activated [24, 27].

CPNs reduce a model's dimension by increasing the abstraction level, allowing tokens to have associated information called colors. In addition, they will enable the information flow to be specified using data assigned to tokens whose values change according to the events that appear. As a result, CPNs allow the construction of more compact and parametric models than the PN, which facilitates their maintenance and subsequent codification [24, 28].

2. 2. Conceptual model

Based on observation, interviews, and feedback from the ER coordinator, the flow of the ER process and its description are presented in **Fig. 1**.

The process begins with the patient's arrival that follows different flows (**Fig. 1**):

1) triage I patients receive immediate medical care in the minor surgery room;

2) triage II patients go directly to triage;

3) triage III and IV patients must go through pre-triage before triage.

Before medical consultation in the physician's office or the minor surgery room (patients with trauma, fractures, and wounds), triage II and III patients gather in a queue for the first or second medical consultation. After the first visit in medical consultation, the patient may require diagnostic tests in the auxiliary room or radiology or leave the ER. For the second medical consultation, some patients wait in the waiting room for lab test results. In contrast, If the nurse channeled, took samples, or applied medicines to the patients, they stayed in the observation room. After the second medical consultation, patients may be directed to observation or leave the ER.

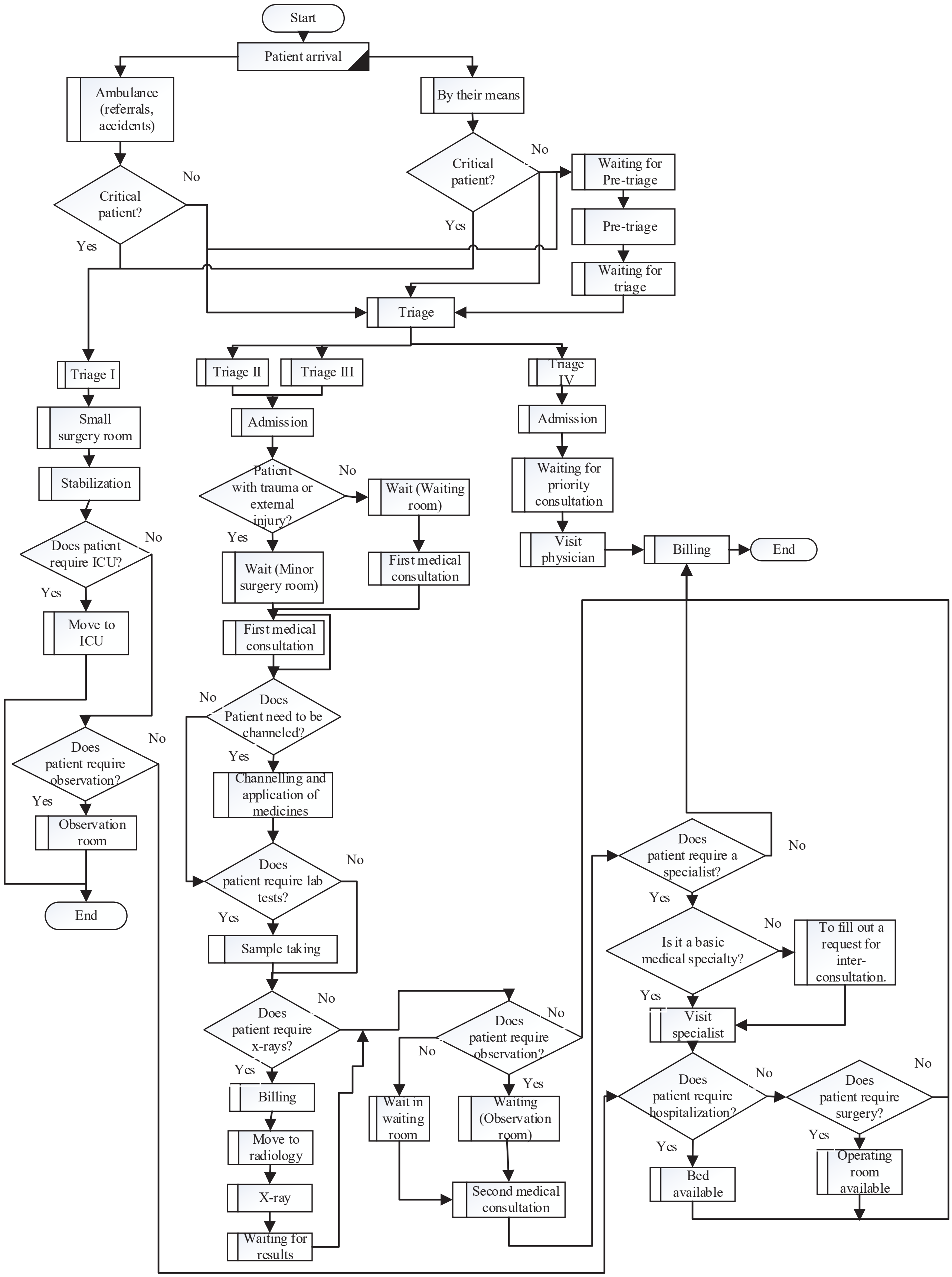

Fig. 1. Flowchart of the adult emergency care process

2. 3. Design and construction of the simulation model

2. 3. 1. Assumptions

The design of the simulation model considered the following assumptions:

1) patients who arrived by ambulance or by their means were treated in the same way in the care process;

2) patients made a maximum of two medical consultations;

3) all physicians are identical in their patient care capabilities;

4) the non-productive time of physicians and care staff was considered, as they spend some time on administrative matters, breaks, and shift change.

2. 3. 2. Model of the hierarchical timed colored Petri net

Fig. 2 presents the general CPN module with ten substitution transitions (double-line rectangle).

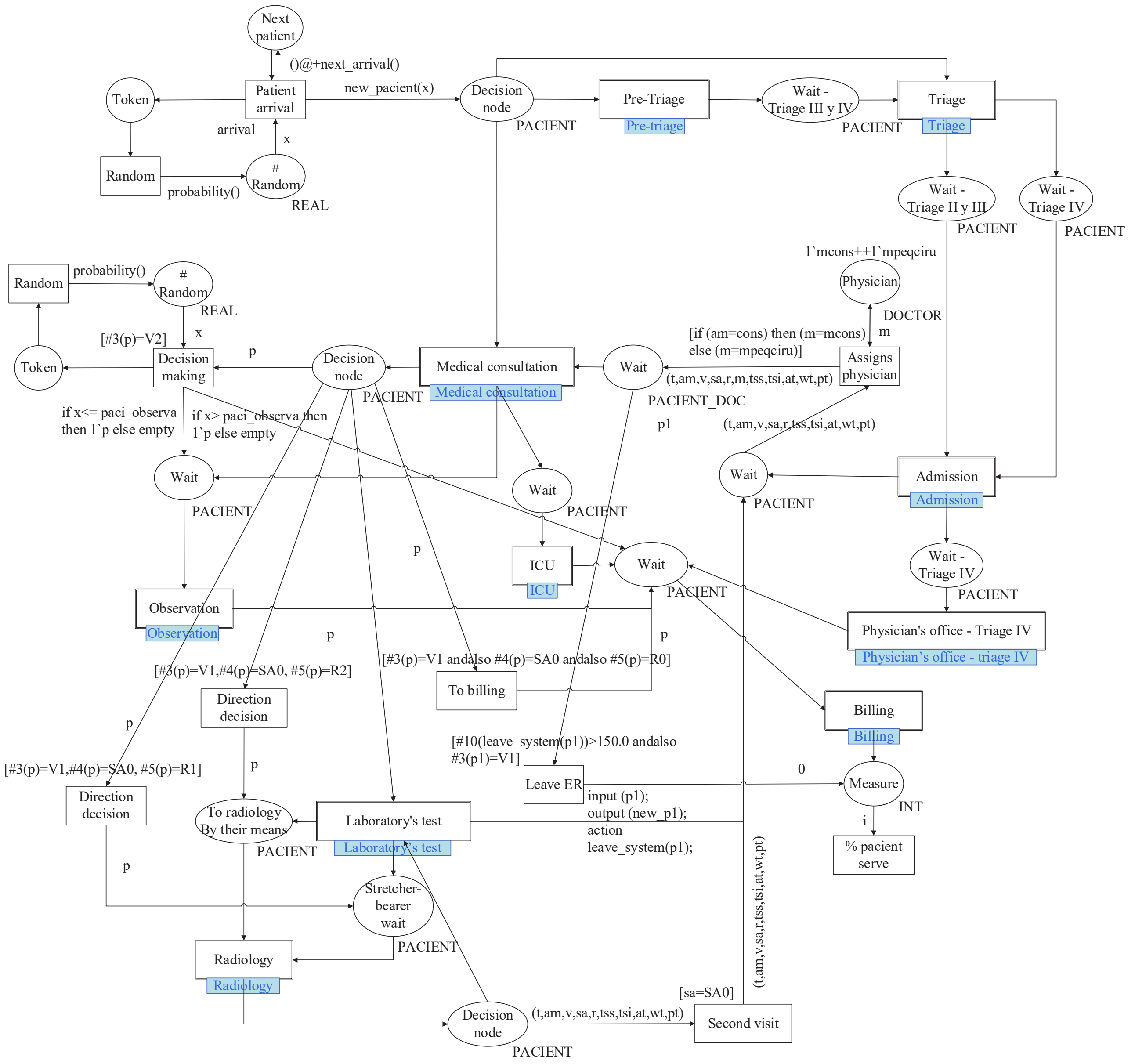

Fig. 2. The general module of the hierarchical timed colored Petri net

The function next_arrival () generates the arrival of a patient that is located at the decision node, which has the color set PACIENT with this tuple (C(PACIENT) = $t,am,v,sa,sa,r,tss,tsi,at,wt,pt$).

The function new_patient(x) randomly assigns the patient priority using the *probability*() function, a variable (x), and a constant value. In string and real format, the variables *tss* and *tsi* show time stamps when a transition can consume a token. The variable *at* indicates the patient arrival time, and the variables *wt* and *pt* store the waiting and in-process times, respectively. After the medical consultation, patients are placed in the decision node and distributed as follows:

1) radiology, both patients transported by the stretcher-bearer and by their means;
2) laboratory tests;
3) patients leaving the system, they do not require diagnostic tests, and going to billing;
4) observation.

In the triage sub-module, triage II patients have higher priority than triage III, and the color of the medical consultation place is assigned (physician's office or minor surgery room). In the admission sub-module patients receive two colors corresponding to laboratory or radiology tests and the first visit to the physician's office. In the Physician place of the medical consultation sub-module (**Fig. 3**) are located the physicians available in the physician's office or minor surgery room (3′(*mcons*)+1′(*mpeqciru*)). Standard priorities were assigned to organize the queue in the start transitions for triage II and III patients. The downtime transitions decreased productive physician time and disregarded an office physician (*mcons*) on the night shift. Finally, at the transition End, triage I patients can be sent to observation or the intermediate care unit (ICU). In the laboratory tests sub-module, patients can go from the auxiliary room to:

1) wait for results in observation or the room;
2) radiology transported by stretcher-bearer or by their means.

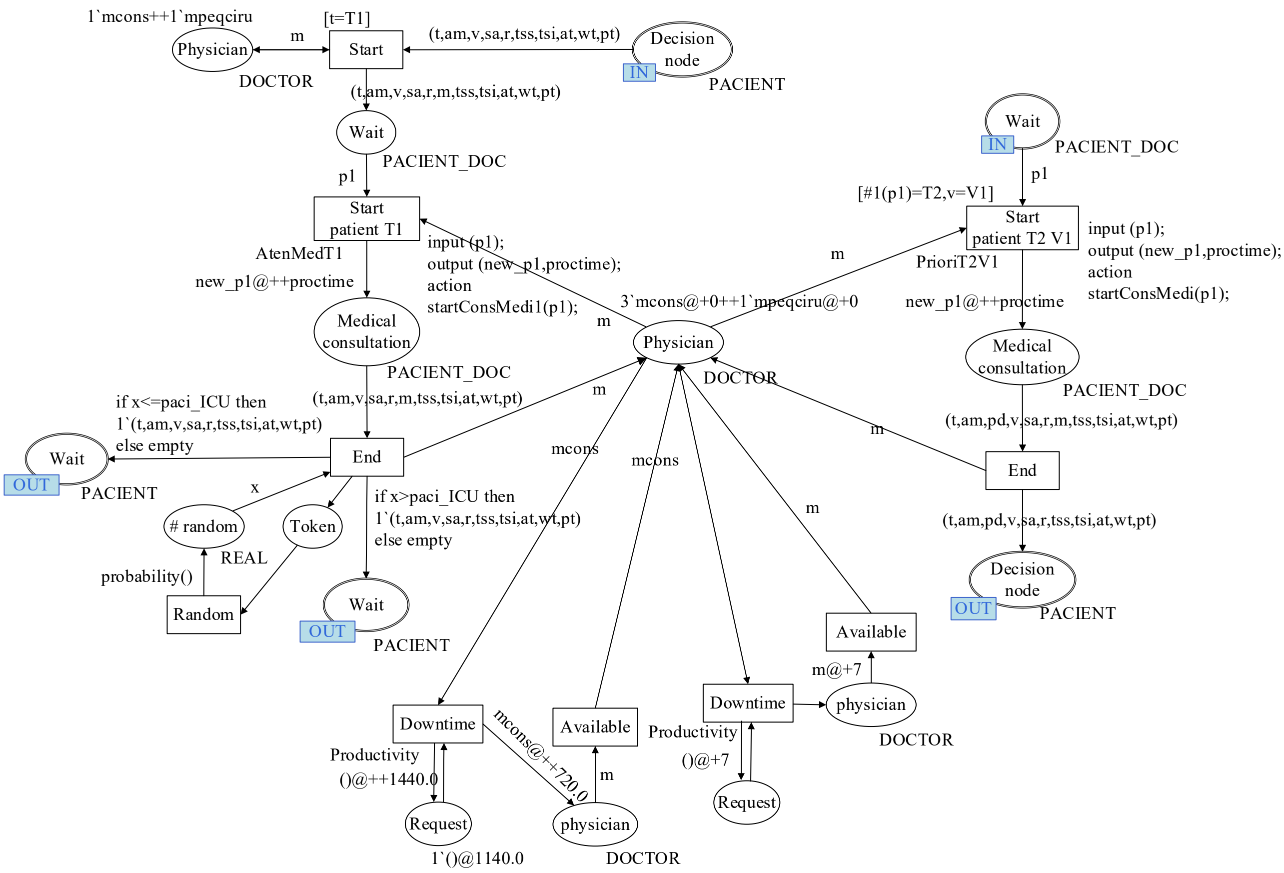

Fig. 3. Medical consultation sub-module

2. 3. 3. Simulation model statements in CPN Tools software

The simulation model declarations in CPN Tools are presented following:

1) Color set.

Simple color set. TR is used to place a random value between [0,1.0] and for the time variables:

colset TR = real.

Subsets construct with a simple color set and «with». Colset with «with» was used to assign available resources (i.e., nurses):

colset enf_triage = with et timed.

Subsets construct with a simple color set and «with». Colset with «with» was also used to define simple enumerations. They take more than one value. i. e., *triage*: Patient priority:

colset triage = with T1|T2|T3|T4.

Compound color sets. PACIENT_DOC product represents the colors of a token. It includes: «*t*» (triage), «*am*» (place of medical care), «*v*» (# office visits), «*sa*» (lab test), «*r*» (radiology), «*m*» (type of physician) «*tss*» and «*tsi*» (time stamp in string and real format), «*at*» (arrival time), «*wt*» (waiting time), «*pt*» (time in process).

Closet PACIENT_DOC = product triage*atencion_medica*visitas*sala_aux*radiologia*medicos*TS*TR*TR*TR*TR timed.

2) Variables are associated with simple color sets, color subsets constructed with the «with» clause, and composite color sets. Variables of type PACIENT_DOC are used as input and output of the transitions functions:

var p1,new_p1:PACIENT_DOC.

3) Constant values are used in the functions on the arc expressions to assign patient triage:

val priority2 = 0.2870.

4) Functions in the arc expressions.

A function used to generate a new patient with the color sets indicating: triage (T1, T2, T3, T4), place of medical care (indefi, cons, peqciru), # visits (V0,V1,V2), room_aux (SA0,SA1,SA2) (laboratory test), radiology (R0,R1,R2). In addition, it assigns the time stamp in string and real format, the arrival time (time()), and the values (0.0) corresponding to the cumulative waiting and processing times:

```
fun new_patient(x) = if x<=priority1 then
1`(T1,indefi,V0,SA0,R0,ModelTime.toString(time()),time(),time(),0.0, 0.0)
else if (x<=priority2 andalso x>priority1) then
1`(T2,indefi,V0,SA0,R0,ModelTime.toString(time()),time(),time(),0.0, 0.0)
else if (x>priority2 andalso x<=priority3) then
1`(T3, indefi,V0,SA0,R0,ModelTime.toString(time()),time(),time(),0.0, 0.0)
else 1`(T4, indefi,V0,SA0,R0,ModelTime.toString(time()),time(), 0.0, 0.0).
```

5) Functions used in the code segments:

```
fun startConsMedi ((t,am,v,sa,r,m,tss,tsi,at,wt,pt):PACIENT_DOC) =
let
val proc_time = (if v = V1 andalso t = T2 then 3.0 + gamma (1.0/12.9, 1.92)
else if v = V1 andalso t = T3 then 3.0 + gamma (1.0/11.8, 1.68)
```

```
else if v = V2 andalso t = T2 then 5.0 + gamma (1.0/3.61, 1.74)
else 5.0 + gamma (1.0/3.61, 1.74))
val time_stamp = time()+proc_time
val new_tss = ModelTime.toString(time_stamp)
val new_tsi = time_stamp
val new_wt = wt+ (time() - tsi)
val new_pt = pt+proc_time
in ((t,am,v,sa,r,m,new_tss,new_tsi,at,new_wt,new_pt),proc_time)
end
```

Val proc_time. Determine the time in the process.
val time_stamp. (the model time when the transition occurs) + (the value of proc_time).
val new_tss. The new value of tss corresponds to the time stamp in string format.
val new_tsi. The new value of tsi corresponds to the stamp time in real format.
val new_pt. The new value of the accumulated process time. (pt + proc_time).
val new_wt. The new value of the accumulated waiting time. Wt + (time() – tsi).

6) Functions used in the guard.
It determines the patients' queue for an observation bed:

$$\text{fun len}(q\text{:Queue\_Observation}) = \text{if } q = [\,] \text{ then 0 else 1+len(tl}(q)).$$

2. 4. Model verification

The simulation model was verified by exploring the system performance through interactive simulation [29].

3. Results and Discussion

3. 1. Case study

This research considered a public hospital of the complexity level third located in Cúcuta, Colombia, that provides emergency services 24/7 with specialized staff.

3. 1. 1. Data collection

Historical data showed that the adult ER cared for 22,246 patients during the first half of 2019, with an average arrival rate of 5.12 patients/hour and an average inter-arrival time of 11.716 min/patient. Also, the patients were identified by priority (triage I = 3.92 %; triage II = 24.78 %; triage III = 61.52 %; triage IV = 9.77 %) and medical consultation and observation times. Interviews with medical and nursing staff established the minimum and maximum times for the other ER processes (**Table 1**). According to [24, 25], the uniform distribution is applicable due to the limited data available. Goodness-of-fit tests were performed with the medical consultation times using Arena's Input analyzer.

Table 1
Probability distributions for each stage of the process

#	Process	Probability distribution
1	2	3
1	Pretriage	Uniform (1.0, 1.5)
2	Triage	Uniform (3.0, 7.0)
3	Admission	Uniform (5.0, 10.0)
4	First medical consultation-triage I	4+Gamma (13.4, 2.16)
5	First medical consultation-triage II	3+Gamma (12.9, 1.92)
6	First medical consultation-triage III	3+Gamma (11.8, 1.68)
7	First medical consultation-triage IV	2+Gamma (7.51, 1.93)

Continuation of Table 1

1	2	3
8	Second medical consultation-triage II or III	5+Gamma (3.61, 1.74)
9	Observation	1+Weibull (2070.0,0.502)
10	UCIM	Uniform (240.0, 1020.0)
11	Channeling and sample-taking	Uniform (8.0, 12.0)
12	X-Ray	Uniform (5.0, 10.0)
13	Waiting for lab results	Uniform (90.0, 180.0)
14	Waiting for x-ray results	Uniform (2.0, 5.0)
15	Transport to or from radiology	Uniform (2.0, 4.0)
16	Billing	Uniform (5.0, 10.0)

Table 2 shows the staff available in the ER, which operates in three shifts. Shifts 1 and 2 are 6 hours starting at 7 am, and shift 3 (night shift) is 12 hours beginning at 7 pm. The observation room has 100 beds, and the ICU has seven beds.

Table 2
Staff available in the emergency room

Process	Staff	Staff per shift		
		1	2	3
Pretriage	Auxiliary nurse	1	1	1
Triage	Chief nurse	1	1	1
Admission	Assistant	1	1	1
medical consultation	Physician	3	3	2
Minor surgery room	Physician	1	1	1
Auxiliary room	Auxiliary nurse	3	3	3
Billing	Assistant	1	1	1
X-Ray	Radiologist	1	1	1
Transport	Stretcher-bearers	3	3	3

The chief nurse and the ER coordinator estimated that after triage, 91 % of the patients go to the physician's office and 9 % to the minor surgery room. After medical consultation, approximately 25 % of the patients receive outpatient treatment. The rest need blood tests, urine tests, x-rays, or a combination of these (**Table 3**). Finally, 75 % of the patients who required diagnostic tests must remain under observation and then be discharged or evaluated by a specialist physician.

Table 3
Required diagnostic tests (constant values)

Identification in CPN Tools	Test	%
SA0-R0	None	25
SA0-R1	X-ray with transport by a stretcher-bearer	18
SA0-R2	X-ray with transport by their means	7
SA1-R0	Sample taking (laboratory)	10
SA1-R1	Laboratory and X-ray with transport by a stretcher-bearer	7
SA1-R2	Laboratory and X-ray with transport by their means	3
SA2-R0	Channeling, medicines, and sample taking or medicines	15
SA2-R1	Channeling, medicines, and sample taking or medicines and X-rays with transport by a stretcher-bearer	10
SA2-R2	Channeling, medicines, and sample taking or medicines and X-rays with transport by their means	5

3. 1. 2. Model validation

This research considered a simulation length of one year (525,600 minutes), a 5 % significance level, and a 5-minute confidence interval for the triage II patient average waiting time, and it was determined that 64 replicates were necessary. The model was validated operationally with historical data from the third quarter of 2019, considering the variable triage II patient's average waiting time for medical consultation [10]. **Table 4** presents the simulated waiting times and their confidence interval, the t-statistic, lower than the critical t-value, 2.042 (30 replicates) and 1.997 (64 replicates), and the p-values. Therefore, with 95 % confidence, there is no significant difference between the means of the simulated and current models.

Table 4
Validation of the average waiting time for triage II patients

# replicates	The current system (min)	Simulated system (min)	Confidence interval 95 % (min)		t-statistic	p-value
30	28.11	26.38	19.09	33.67	0.4652	0.2598
64	28.11	26.43	21.55	31.31	0.6742	0.2555

3. 2. Simulation improvement scenarios

This paper proposed several scenarios with the help of the ER coordinator, and **Table 5** shows the results of the 64 replications in each scenario concerning the KPI considered.

The base scenario (*A*) considered the current situation of the ER, and it was used for model operational validation. Scenario (*A*1) considered the baseline scenario and added internal physicians (interns) to support the medical consultation, which would reduce time by 25 % (According to the ER coordinator). Scenario (*A*2) considered the baseline scenario and added a physician in the minor surgery room for shifts 1 and 2. Scenario (*A*3) assumed scenario (*A*2) and added a physician for each office and the minor surgery room from 7 to 10 pm. Finally, scenario (*A*4) combines scenarios *A*1 and *A*3, and scenario (*A*5) considered the increase in the patient arrival rate by 25 %.

Scenarios *A*6 to *A*9 required modification of the simulation model (**Fig. 2**) in the observation process (**Fig. 4, 5**). Scenario (*A*6) considered the baseline scenario and included the current 100 observation beds as a limited resource (**Fig. 5**). In addition, a maximum queue of 20 patients waiting for a bed (len(*q*) >= 20) (20 wheelchairs available) would be allowed (**Fig. 4**) before the ER diverts patients to other ERs. Scenarios *A*7 through *A*9 considered scenario *A*6, and the bed capacity was 150, 160, and 200, respectively.

Table 5
Simulation results of the improvement scenarios

A	Average waiting time (min)						H	I	J	K	L	M
	B	C	D	E	F	G						
A	26.43	24.56	53.37	49.91	49.27	58.34	10.54 %	147.36	3.85	–	–	–
A1	23.58	21.99	42.25	38.6	37.96	45.82	4.44 %	159.65	2.4	–	–	–
A2	24.67	23.75	36.22	45.55	46.14	38.84	8.95 %	150.52	3.29	–	–	–
A3	23.14	22.44	31.25	41.29	41.98	33.9	6.47 %	155.01	2.69	–	–	–
A4	20.96	20.31	27.98	32.62	32.77	32.97	2.67 %	162.79	1.65	–	–	–
A5	30.88	29.03	63.36	64.01	63.5	71.67	21.34 %	158.21	6.74	–	–	–
A6	25.45	23.54	49.9	45.25	44.54	53.75	38.91 %	99.24	2.12	99.24 %	17.13	693.07
A7	26.41	24.48	53.18	49.55	48.9	57.98	13.49 %	142.16	3.78	94.77 %	4.54	128.12
A8	26.43	24.51	53.3	49.89	49.23	58.55	11.49 %	146.38	3.93	91.49 %	1.89	52.31
A9	26.51	24.6	53.59	50.05	49.4	58.5	10.53 %	147.65	4.02	73.83 %	0	0

Note: A – scenarios; B – triage II; C – triage II – office; D – triage II – minor surgery room; E – triage III; F – triage III – office; G – triage III – minor surgery room; H – left without being seen by a physician; I – the average number of patients under observation; J – the average queue for medical consultation; K – beds utilization rate in observation; L – the average queue in observation; M – average waiting time for an observation bed

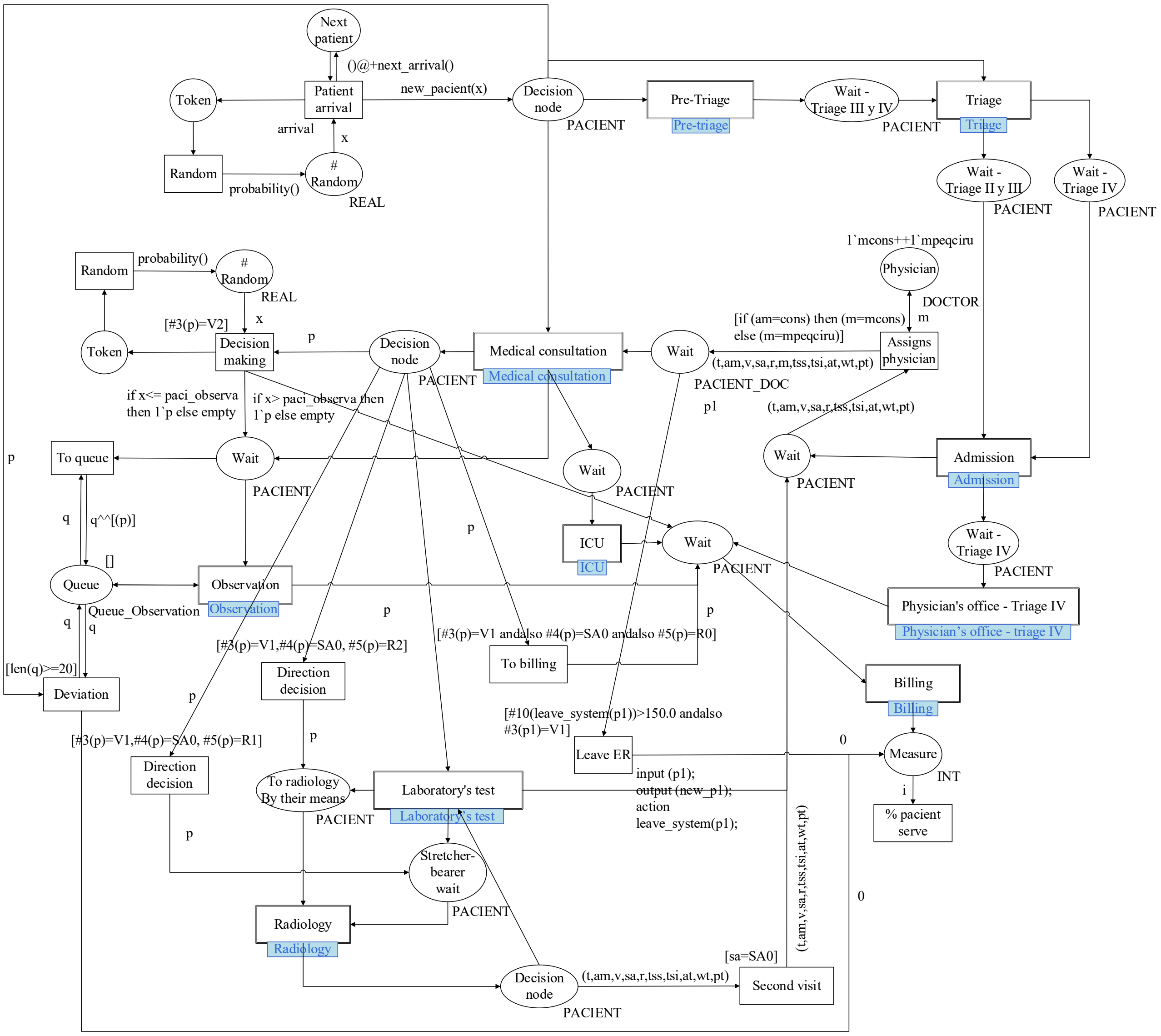

Fig. 4. The general module of the hierarchical timed colored Petri Net – modified

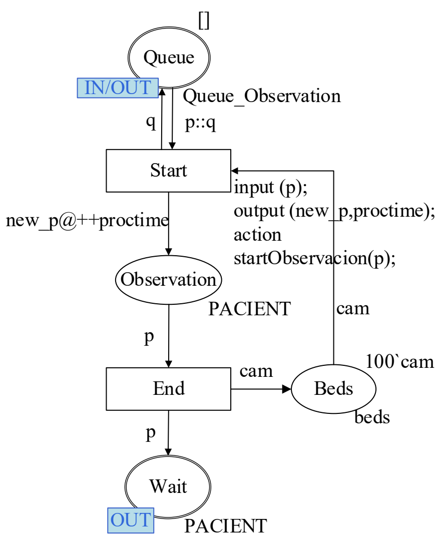

Fig. 5. Observation sub-module

Table 5 shows scenario *A*4 gets the best performance since it reduces the average waiting times for triage II patients by 17.30 % and 47.57 %, and triage III by 33.49 % and 43.49 %, to medical consultation in the office or the minor surgery room, respectively. Likewise, it reduced the queue in consultation medical and LWBS by 57.14 % and 74.67 %, respectively. Scenario (*A*6) reduced the waiting time; however, this is not an improvement since, when including the 100 observation beds with limited capacity and a maximum queue of 20 patients waiting for a bed, the LWBS increases by more than three times (**Table 5**).

Scenario A4 estimates a reduction in triage II patient waiting time from 53.37 to 27.98 minutes for medical consultation in the minor surgery room; therefore, the ER would meet the maximum waiting time (30 minutes) established in Colombian legislation [10]. In addition, the estimated reduction in triage III patient waiting times and the LOS would generate benefits such as increased patient satisfaction, the reception of new patients, and improved efficiency and service.

In scenarios *A*2 through *A*4, which include a physician in the minor surgery room and adjusting the working hours, they reduce the average waiting times for triage II and III patients. Similarly, [16] decreased waiting time by 16 % by adding a physician, and [13] reduced average patient waiting time by 20 to 64 % by adjusting physicians' shifts.

Physicians and chief nurses in triage presented low utilization and decreased scenarios with more resources. However, the simulation model considered that physicians are not available 100 % of the time, as they spend some time filling out the information, breaks, and shift changes. The ER coordinator validated the utilization of medical staff in the base scenario.

LOS is unaffected in scenarios *A*1 to *A*4 and increases in *A*6 to *A*9. The long LOS is due to factors related to the Colombian health system, which affects public hospitals. Some health insurers do not authorize diagnostic tests, surgeries, hospitalization, referral to a hospital of a higher complexity level, or have debts with the hospital. Therefore, patients must remain in observation instead of hospitalization. It is proposed to reduce the observation time; however, it was impossible to evaluate it due to the difficulty of incorporating external factors related to the Colombian health system in the simulation. The prolonged LOS in the ER case study is also in other public hospitals. [3, 30] concluded the main failures of the Colombian health system affecting LOS are the difficulty in referring patients to another complex level and the delay in authorizations by insurance companies.

Scenarios *A*6 to *A*9 were used to plan the number of required observation beds. Increasing the bed number to 160 reduces the average patient queue by 88.97 % and the waiting time for a bed by 92.45 %. In addition, the KPIs in the base (*A*) and A8 scenarios are similar; therefore, the number of observation beds should be 160 to avoid the current situation of patients on chairs or the floor.

Finally, the results obtained serve as recommendations, especially scenarios *A*4 and *A*8, for the ER coordinator to present to hospital management for medical staff planning and the requirement for investment in observation beds to improve KPI. The design simulation model can be applied to the ER of hospitals of any complexity level or trauma level (EE.UU). However, as a future study, the model could include the care of specialist physicians and an additional color related to the patient's insurer. Also, include the analysis of other resources and costs required.

4. Conclusions

This research aimed to design a detailed patient flow model to improve emergency room performance using the hierarchical timed CPN. The model was simulated to evaluate scenarios leading to improvement in ER KPI. Scenario *A*4 obtained the best performance as it reduced the average waiting times for triage II patients by 17.30 % and 47.57 %, and triage III by 33.49 % and 43.49 %, to medical consultation in the office or the minor surgery room, respectively. Likewise, it reduced the queue in consultation medical and LWBS by 57.14 % and 74.67 %, respectively. Moreover, the designed simulation model presents greater detail than the literature since it included more attributes (colors) to patients concerning the place of medical care in the ER, the number of visits to the physician, and the physician who will care for the patient.

The initial simulation model (**Fig. 2**) was modified to scenarios *A*6 to *A*9 and used to plan the required observation beds. Increasing the bed number to 160 (Scenario *A*8) reduces the average patient queue by 88.97 % and the waiting time for a bed by 92.45 %. In addition, the KPI in the base (A) and $A8$ scenarios are similar; therefore, the number of observation beds should be 160 to avoid the current situation of patients on chairs or the floor and improve the quality of emergency services.

The designed model was used to improve KPI by evaluating scenarios that considered tactical decisions such as physician personal planning, operational decisions such as adjusting work schedules, and strategic decisions such as increasing observation beds. The proposed model helps ER managers make decisions to address problems such as ER overcrowding, long LOS, high LWBS rates, and patient dissatisfaction. These results improve the quality and timeliness of the service and avoid putting the patient's health and life at risk.

Conflict of interest

The authors declare that there is no conflict of interest in relation to this paper, as well as the published research results, including the financial aspects of conducting the research, obtaining and using its results, as well as any non-financial personal relationships.

Financing

The study was performed without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Acknowledgments

The authors thank the hospital for their support in developing the research.

References

[1] Derni, O., Boufera, F., Khelfi, M. F. (2019). Coloured Petri net for modelling and improving emergency department based on the simulation model. International Journal of Simulation and Process Modelling, 14 (1), 72. https://doi.org/10.1504/ijspm.2019.097717

[2] Salimifard, K., Hosseini, S., Moradi, M. (2013). Improving Emergency Department Processes Using Coloured Petri Nets. Joint Proceedings of the International Workshop on Petri Nets and Software Engineering (PNSE'13) and the International Workshop on Modeling and Business Environments (ModBE'13) co-located with the 34th International Conference on Application and Theory of Petri Nets and Concurrency Petri Nets 2013. Vol. 989. Milano, 335–349. Available at: https://ceur-ws.org/Vol-989/paper02b.pdf

[3] Caicedo, A., Rivera, L. (2021). Caracterización de los servicios de urgencias de una ciudad fronteriza colombiana. Emergencia, 33, 239–241. Available at: https://revistaemergencias.org/wp-content/uploads/2023/08/Emergencias-2021_33_3_239-241.pdf

[4] Aboueljinane, L., Frichi, Y. (2022). A simulation optimization approach to investigate resource planning and coordination mechanisms in emergency systems. Simulation Modelling Practice and Theory, 119, 102586. https://doi.org/10.1016/j.simpat.2022.102586

[5] MSPS, M. de S. y P. S. (2019). Observatorio nacional de Calidad en Salud, Indicadores de calidad resolución 0256/16.

[6] Ashour, O. M., Okudan Kremer, G. E. (2014). Dynamic patient grouping and prioritization: a new approach to emergency department flow improvement. Health Care Management Science, 19 (2), 192–205. https://doi.org/10.1007/s10729-014-9311-1

[7] Ajami, S., Ketabi, S., Yarmohammadian, M., Bagherian, H. (2012). Wait Time in Emergency Department (ED) Processes. Medical Archives, 66 (1), 53. https://doi.org/10.5455/medarh.2012.66.53-57

[8] Luscombe, R., Kozan, E. (2016). Dynamic resource allocation to improve emergency department efficiency in real time. European Journal of Operational Research, 255 (2), 593–603. https://doi.org/10.1016/j.ejor.2016.05.039

[9] Ibrahim, I. M., Liong, C.-Y., Bakar, S. A., Ahmad, N., Najmuddin, A. F. (2017). Minimizing patient waiting time in emergency department of public hospital using simulation optimization approach. AIP Conference Proceedings. https://doi.org/10.1063/1.4980949

[10] M. de S. y P. S. MSPS (2015). Resolución 5596 del 2015. Por la cual se definen los criterios técnicos para el Sistema de Selección y Clasificación de pacientes en los servicios de urgencias 'Triage'.

[11] Kuo, Y.-H., Rado, O., Lupia, B., Leung, J. M. Y., Graham, C. A. (2014). Improving the efficiency of a hospital emergency department: a simulation study with indirectly imputed service-time distributions. Flexible Services and Manufacturing Journal, 28 (1-2), 120–147. https://doi.org/10.1007/s10696-014-9198-7

[12] Diefenbach, M., Kozan, E. (2011). Effects of bed configurations at a hospital emergency department. Journal of Simulation, 5 (1), 44–57. https://doi.org/10.1057/jos.2010.1

[13] Sinreich, D., Jabali, O., Dellaert, N. P. (2012). Reducing emergency department waiting times by adjusting work shifts considering patient visits to multiple care providers. IIE Transactions, 44 (3), 163–180. https://doi.org/10.1080/0740817x.2011.609875

[14] Ershadi, M. M., Shafaeizadeh, A. (2021). Simulation-based improvement and modification for performances of hospitals: a case study. International Journal of Simulation and Process Modelling, 16 (2), 90. https://doi.org/10.1504/ijspm.2021.115857

[15] Doudareva, E., Carter, M. (2021). Using Discrete Event Simulation to Improve Performance At Two Canadian Emergency Departments. 2021 Winter Simulation Conference (WSC). https://doi.org/10.1109/wsc52266.2021.9715411

[16] Bedoya-Valencia, L., Kirac, E. (2016). Evaluating alternative resource allocation in an emergency department using discrete event simulation. SIMULATION, 92 (12), 1041–1051. https://doi.org/10.1177/0037549716673150

[17] Zhao, Y., Peng, Q., Strome, T., Weldon, E., Zhang, M., Chochinov, A. (2015). Bottleneck detection for improvement of Emergency Department efficiency. Business Process Management Journal, 21 (3), 564–585. https://doi.org/10.1108/bpmj-06-2014-0060

[18] Cocke, S., Guinn, D., MacBlane, E., Walshak, S., Willenbrock, N., White, K. P. et al. (2016). UVA emergency department patient flow simulation and analysis. 2016 IEEE Systems and Information Engineering Design Symposium (SIEDS). https://doi.org/10.1109/sieds.2016.7489282

[19] Daldoul, D., Nouaouri, I., Bouchriha, H., Allaoui, H. (2015). Optimization on human and material resources in Emergency Department. 2015 International Conference on Industrial Engineering and Systems Management (IESM). https://doi.org/10.1109/iesm.2015.7380224

[20] Hoot, N. R., LeBlanc, L. J., Jones, I., Levin, S. R., Zhou, C., Gadd, C. S., Aronsky, D. (2008). Forecasting Emergency Department Crowding: A Discrete Event Simulation. Annals of Emergency Medicine, 52 (2), 116–125. https://doi.org/10.1016/j.annemergmed.2007.12.011

[21] Lee, S. (2014). The role of hospital selection in ambulance logistics. IIE Transactions on Healthcare Systems Engineering, 4 (2), 105–117. https://doi.org/10.1080/19488300.2014.914608

[22] Castanheira-Pinto, A., Gonçalves, B., Lima, R. M., Dinis-Carvalho, J. (2021). Data Modelling and Validation of An Emergency Department Simulation Model-A Lean Healthcare Approach. Industrial Engineering and Operations Management, 1–11. https://doi.org/10.1007/978-3-030-78570-3_1

[23] Hosseini, S. M., Mohammadi, K., Yaghoubi, M. (2022). Optimization of Service Process in Emergency Department Using Discrete Event Simulation and Machine Learning Algorithm. Arch. Acad. Emerg. Med., 10 (1), e44.

[24] Guasch Petit, A., Piera Eroles, M. A., Casanovas Garcia, J., Figueras Jové, J. (2003). Modelado y simulación : aplicación a procesos logísticos de fabricación y servicios. https://doi.org/10.5821/ebook-9788498802351

[25] Banks, J., Carson, J. (1984). Discrete-event system simulation. New Yersey: Prentice Hall, INC.

[26] Ghomri, L., Alla, H. (2018). Continuous Petri nets and hybrid automata: two bisimilar models for the simulation of positive systems. International Journal of Simulation and Process Modelling, 13 (1), 24. https://doi.org/10.1504/ijspm.2018.090264

[27] van der Aalst, W. M. P., Stahl, C. (2011). Modeling Business Processes. The MIT Press. https://doi.org/10.7551/mitpress/8811.001.0001

[28] Barad, M. (2003). Tutorial and Survey Articles: An introduction to Petri Nets. International Journal of General Systems, 32 (6), 565–582. https://doi.org/10.1080/03081070310001623366

[29] Jensen, K., Kristensen, L. M. (2009). Coloured Petri Nets. Springer Berlin Heidelberg. https://doi.org/10.1007/b95112

[30] Ceballos-Acevedo, T. M., Velásquez-Restrepo, P. A., Jaén-Posada, J. S. (2014). Duración de la estancia hospitalaria. Metodologías para su intervención. Gerencia y Políticas de Salud, 13 (27). https://doi.org/10.11144/javeriana.rgyps13-27.dehm

Received date 23.06.2023
Accepted date 06.01.2024
Published date 31.01.2024

How to cite: *Caicedo-Rolon, A. Jr., Guerrero-Gomez, G., Moreno-Gamboa, F. (2024). Design of a model for improving emergency room performance using a colored Petri net. EUREKA: Physics and Engineering, 1, 154–166. doi: https://doi.org/10.21303/2461-4262.2024.002979*