A Coloured Petri Net-based approach and Genetic Algorithms for improving services in the Emergency Department

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Abstract

The Emergency Department (ED) plays an important role in the healthcare field, due to the nature of the services it provides, especially for patients with urgent cases. Therefore, good management of ED is very important in improving the quality of services. Good management depends on the effective use of material and human resources. One of the most common problems that the ED suffers from is the long waiting period and the length of the patient's stay. Many researchers have proposed many solutions to reduce waiting time and length of stay (LOS). One of the best solutions for resource optimization is modeling and simulation based on inputs such as patient length of stay and door-to-doctor time (DTDT). In this study, the ED was modeled using a Coloured Petri Net, and to determine the number of resources needed, genetic algorithms were used. This study was conducted in the ED of Hassani Abdelkader Hospital in Sidi Bel Abbes, and several simulation models were evaluated, which reduced the waiting time and the length of stay for the patient.

Keywords: emergency department (ED), system modelling, Coloured Petri Net, genetic algorithms, optimization.

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1 Introduction

Health is the basic asset of human beings, and the healthcare system usually meets the health needs of the population of any country.

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Hospitals are the most important component of the healthcare service network, and the emergency department (ED) is an important component of the hospital [1]. As the years pass, the population increases, new diseases appear with different symptoms, the difficulty of predicting critical situations, and the limited resources, all these obstacles stand in the way of decision-makers [2]. The patient arrives at the ED in different cases, from critical, non-critical, and semi-critical, to other cases. The models for classifying patients change from one country to another, and the organizational structure may be variable from one country to another, but it shares several characteristics, such as staff nurses, treatment rooms, and medical and laboratory equipment. The process of patient flow is as follows: registration, triage Medical examinations, and additional tests [3].

Among the most common problems is the long waiting time, this problem leads to dissatisfaction among patients, as the patient is always looking for the quality of service. Time is a valuable asset for the patient in seeking treatment in any center, whether private or public, especially for patients with special cases [5].

The ED has recently faced several problems, which negatively affect the workflow. Among the problems that the ED suffers from is the random flow of patients, which causes overcrowding, and this leads to the length of the patient's stay in the ED [6]. The ED is the main entrance to the hospital; despite this, it suffers from several limitations, for example, limited resources and budget. For this purpose, those in charge of the ED work to increase the capacity of the ED to accommodate the largest number of patients by increasing the number of material and human resources [7].

All these factors attracted the attention of many researchers in the field of healthcare and led to a reconsideration of the work policy and the structure of the ED [8]. To improve the quality of service in the ED, the researchers relied on many approaches, where different techniques were used such as demand management, mapping, queuing systems, agent-based systems, and simulation [9].

The ED depends on employing highly qualified doctors and nurses, who are able to face any emergency that may occur at any time because the time factor plays a major role in saving lives [10]. The outbreak of the COVID-19 virus led to many problems for the ED, as it greatly affected the workflow of the medical staff, which led to a review of the ED management policy [11].

Nowadays, simulation is the most widely used method in healthcare management. Simulations have been successfully used in many different areas such as the medical sector, manufacturing, system services, supply chain, transportation, etc. In addition, the simulation method is one of the best ways for decision-makers to evaluate, analyze, and review any operating systems from the simplest to the most complex in order to solve the problems they contain [5]. The most important key element of the simulation is the selection of a key performance indicator (KPI). Although there are no metrics that define a KPI, the most commonly used in this field are average waiting times, length of patient stay (LOS), and the number of patients who leave the ED without medical and nursing advice [3].

In this study, we do a case study of the ED of Sidi Bel Abbes hospital. System modeling is required due to the complexity of the study system. For this purpose, we have relied on a Coloured Petri Net, which is more used to model complex and synchronous systems. Coloured Petri Net tools are used in the simulation in order to simulate the flow of patients and make adjustments to the system before applying it in its real environment. This research is organized as follows. In Section 2, we look at some of the literature studies conducted in emergency departments. In Section 3, the paths that patients take in the ED are explained. In Section 4, we present a research methodology that includes an explanation of KPIs, a brief definition of Coloured Petri Net, a presentation of simulation model, and the use of genetic algorithms to identify resources in the emergency department. In subsection 4.5, simulation results for the proposed models are explained and discussed. In the last section, we present a general conclusion of the research with proposing future solutions.

2 Background and Literature review

Nowadays, several studies have been established based on simulation [11, 12, 13], especially in the field of healthcare. Simulation has become a wide field of research, especially with the ED [14]. Simulations are of great help in several issues such as process identification, process modeling, identification of patient profiles, planning, mastering and optimizing flows, and trial-by-performance [15].

For optimal resource planning in emergency departments, Yousefi et al. (2018) [4] relied on genetic algorithms; in order to solve the problem of overcrowding and patient length of stay, agent-based simulation and machine learning were relied on. Scheduling patient admission is a major problem for the emergency department, and Ceschia and Schaerf (2012) [16] worked on this problem by proposing solutions while considering many real-world features, such as uncertainty in length of stay, presence of emergency patients, and the possibility of late admission. A metaphysical approach is proposed that solves both versions Static and dynamic, depending on the complex neighborhood structure and simulated annealing. This approach gave good results, as it was possible to schedule and accept a large number of patients.

In another work carried out by Ceschia and Schaerf (2016) [17] for the patient's admission process, the scheduling problem was reconsidered in order to be suitable for practical applications. The restrictions imposed on the use of operating rooms for critically ill patients, who require surgery, were taken into consideration. A new model is proposed that includes a flexible planning horizon, new components of the objective function, and a complex concept of patient delay. The local search method is based on the use of a search space based on a complex neighborhood. Statistical distributions and real-world data are used to compile challenging and realistic case studies. Allocating beds in emergency departments requires careful scheduling from the medical staff.

Demeester et al. (2010) [18] have developed a hybrid algorithm based on Tabu search algorithms, the aim of which is to appropriately allocate beds in emergency departments, taking into account the medical needs of patients. Simulation modeling is one of the best methods used for improvement in ED. This method is relied on by Nas and Koyuncu (2019) [1] for improvement. The aim is to optimally determine the number of beds. ED data is analyzed and arrival times and features related to the patient's arrival at the hospital are studied. To analyze this data, ten algorithms for machine learning (ML) were used. The proposed model gave good results, reduced LOS by 7%, and improved the number of beds in ED.

There are a variety of methods and techniques used for improvement in healthcare. Among the methods used is a simulation; the latter has been relied upon by many researchers, including Kittipittayakorn and Ying (2016) [19]. A simulation model was created with the aim of reducing the long waiting time of the patient, the patient's behaviors were studied and modeled to be incorporated into the simulation, and huge data was used. This study gave good results that led to a significant reduction in waiting time.

Simulation has a major role in improving. Gül and Guneri (2012) [20] created a simulation model for discrete events for the emergency department, through which all daily operations were modeled and analyzed. The goal of this work is the optimal use of human and material resources. Another work done by Lamiri et al. (2009) [21] uses mixed integer programming with Monte Carlo simulation. This work aims to organize the surgical operations in the emergency department well.

In a study conducted by Yousefi et al. (2018) [4] in the ED, using agent-based simulation modeling, medical staff allocate human resources to different departments based on experience, or depending on decision support tools. In this study, all staff agents participate in the decision-making process. In modeling, all the components belonging to the ED take part, including patients, doctors, and staff. To assess the behavior of the system, several scenarios were evaluated, and in each scenario, the KPIs were evaluated. Agent-based simulations led to well-organized operations in the emergency department, reducing waiting time.

To study the relationship between the ED and other departments, Yousefi et al. (2017) [3] proposed an integrated approach based on Discrete Event Simulation (DES) and System Dynamics (SD), through which the complexities and interactions between sub-units and emergency departments are revealed. This simulation is known as hybrid simulation, which helps to better understand the ED operations.

3 Patient Management Flowchart

In Figure 1, we show all the paths that the patient follows in the emergency department. Based on this diagram, we build a simulation model. The patient arrives at the ED either by his own means or by ambulance. The patient undergoes the triage process by the triage nurse. Based on the patient's condition, two cases are classified, critical and non-critical. In this study, we rely on the emergency severity index (ESI); the critical condition is classified in the first level, and non-critical cases are classified in other levels (5, 4, 3, and 2).

Patients in critical condition are transferred directly to the operating room. If the surgery is successful, the patient remains in the recovery room and then in the short stay unit for a period of time. It does not exceed 24 hours, then the patient is transferred to another department. Some patients in a non-serious condition need a nursing consultation, while the majority of patients are referred to a normal medical consultation; some cases need a special medical consultation. During a private medical consultation, most cases need additional tests. After obtaining the results of the additional tests, the specialist Doctor decides to either direct the patient to another department of the hospital or to be discharged from the emergency department.

4 Methodology

In this section, we will explain the methodology in detail. After a good study of the behavior and characteristics of the system and using the expertise of the medical staff, we model the ED through a Coloured Petri Net and develop a genetic algorithm that helps us greatly to determine the number of resources used in the emergency department by entering new resources into the model and comparing the results.

4.1 Key performance indicator

To evaluate any system, we use KPIs, which the system has as its own characteristics. In this study, we evaluate the ED using door-to-doctor time (DTDT) and length of stay (LOS). These are the most commonly used KPIs in healthcare. Below we explain these indicators:

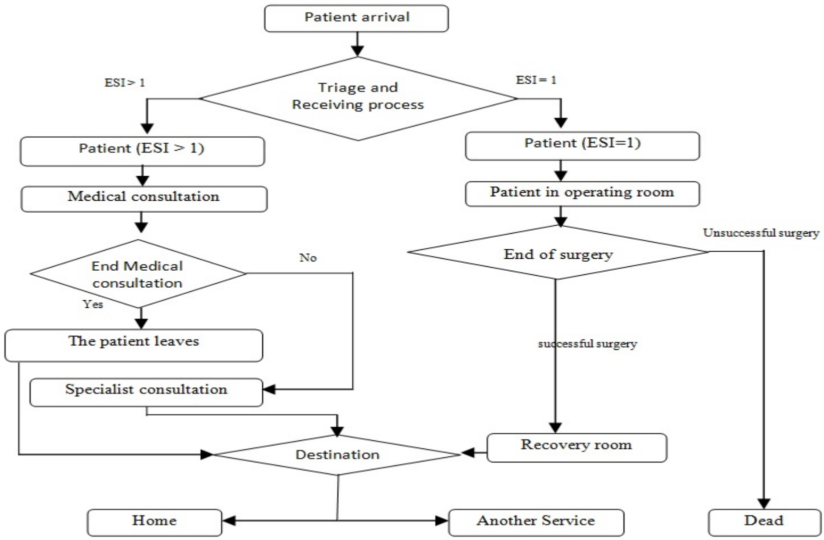

Figure 1. Patient path in the emergency department

- Length of stay (LOS): The time a patient spends in the emergency department, from admission to departure at home, or to another section of the hospital.

- Door-to-doctor time (DTDT): The amount of time that a patient spends from entering the ED to the first medical consultation.

4.2 Simulation model

The simulation model was created by our study of the behavior of the system, and with the help of medical and administrative staff. Figure 2 shows the basic elements of the model. The most important basic elements of the model are the triage process, general and specialist medical consultation, additional tests, surgery, and patient orientation. Through the model, each place represents the situation in which the patient may be. The paths that the patient takes vary according to the condition, from critical to non-critical, nursing, medical and special consultation. Table 1 shows the places of the simulation model, Table

2 shows the transitions. Patient access to the ED is designed by a token in the place the patient has accessed. This place is characterized by a set of PATIENT colors. The latter includes a set of attributes for calculating the duration of operations for all stages, waiting times, LOS and DTDT. In this model, we use P and P2 as variables of a PATIENT type. These variables are used as inputs and outputs for the transitions' functions. Patient access is modeled by an exponential distribution function with a mean of 8.5, this parameter is calculated based on the data collected. ESI is used on each patient in the triage process.

The simulation model includes several transitions; each transition is characterized by four properties, the name of the transition, the delay expression, the guard, and the code segment expression. After recording the patient's data, he undergoes the triage process to be classified into two categories, critical and non-critical cases. We use several functions in the model such as the triage function (Reception_time), and the function of calculating the duration of medical advice (MC_Time). The functions are used to calculate times at different stages as well as update the characteristics of a patient's color set. The tokens during their transitions may be subject to a guard function, for example, according to ESI values, the patient is graded. The model is validated by sharing the opinions of clinicians and staff and comparing the output of the model Simulation with real data.

4.3 Resource identification using the genetic algorithm model

In this section, we use genetic algorithms to determine the number of appropriate human resources in the ED. We rely on calculating the average period of time that the patient spends in the following four stages: nursing consultation, medical consultation, specialized medical consultation, and additional tests. The average total time period for the patient is the sum of the four time periods mentioned above. The initial population represents the number of human resources for each emergency phase. Figure 3 shows an example of the initial population:

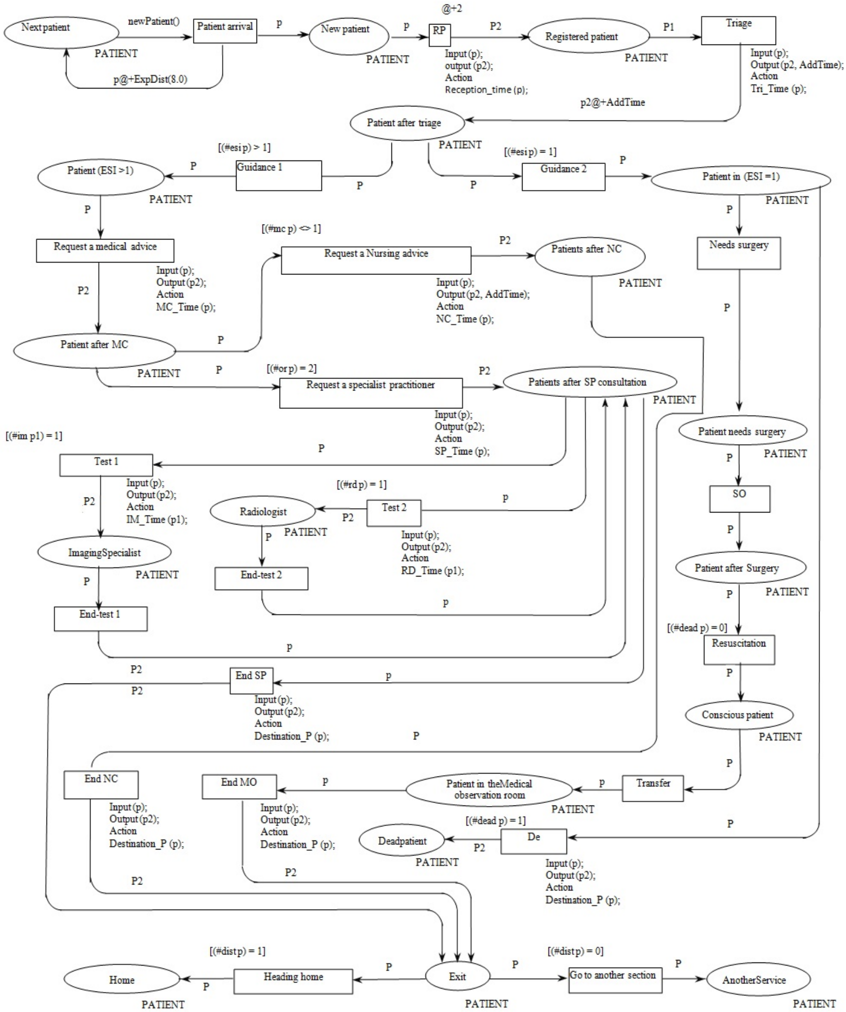

Figure 2. Simulation model using Coloured Petri Nets for ED

Table 1. Place description of the simulation model

Place	Description
New patient	Patient coming to the emergency department
Registered patient	A patient registered in the reception register
patient after triage	The patient after the screening process with his classification according to the case
Patient (ESI 1)	A patient in a non-critical condition
Patient in (ESI =1)	A patient is in a critical condition
Patient after MC	Patient after medical consultation
Patients after NC	Patient after nursing consultation
Radiologist	Patient at the radiologist
Imaging Specialist	Patient at the Imaging Specialist
Patient needs surgery	Patient in the operating room
Patient after Surgery	Patient in the first recovery room
conscious patient	A patient in the second recovery room
Patient in theMedical observation room	Patient in the medical observation room
Dead patient	A patient died after a failed surgery
Exit	A patient finished his visit to the emergency department
Home	The patient goes home
Another Service	The patient goes to another section

Table 2. Description of simulation model transitions

Transition	Description
Patient arrival	Admission of the patient to the emergency department
RP	Registration of the patient in the emergency department
Triage	Triage process
Guidance 1, Guidance 1	Directing the patient to the various sections in the emergency department
Request a Nursing advice	
Request a specialist practitioner	The beginning of a specialized medical consultation
needs surgery	Beginning of the nursing consultation
Test 1, Test 1	Additional exams start
End-test 1, End-test 2	End of additional exams
SO	Surgery process
Resuscitation	Resuscitation process
Transfer	Transfer the patient to the medical observation room
End NC, End SP, End MO	The end of medical and nursing consultations
De	The death of the patient

$$Min\ LOS = \sum_{i=1}^{N} A\_los(x(i)). \quad (1)$$

- N : Number of Resources (For the case studied N=4).
- i : Index of a Resource; i = 1; 2; : : : N;
- x(i) : Resources available at every ED stage, for example: if x(1) = 2, we have two nurses in the nursing consultation stage. For the case studied, x(1) represents the number of nurses, x(2) – the number of general doctors, x(3) – the number of specialist doctors, and x(4) – the number of radiologists.
- *A_los*: A function that calculates the average length of time a patient spends in the resource i. The goal of this function is to find the lowest value of LOS, with the appropriate number of Human Resources. We run the genetic algorithms three times, and each time we obtain new solutions. Tables 4, 5, and 6 represent the results obtained by implementing the genetic algorithms. We modify the number of Human Resources obtained in the simulation model, run the simulation model again, and compare Results every time.

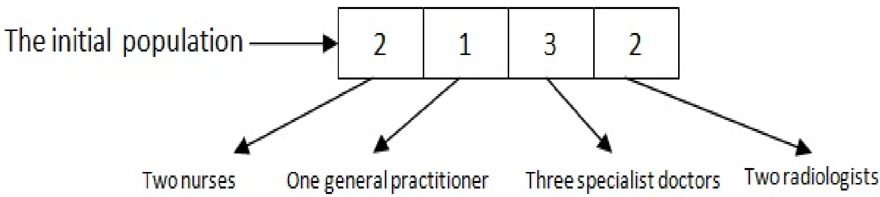

Figure 3. Example of the initial population

4.4 Simulation Results and Discussion

During the study of the behavior of the system, we noted that the most exploited resources in the ED are general and private medical advice, nursing, and additional tests. As for the reception and sorting resource, the time period remains constant and small. The goal of this study is to reduce LOS and DTDT. After developing the prototype by means of a Coloured Petri Net, we ran it for the first time and recorded the initial data. The Coloured Petri Net model is run by CPN tools, which are tools used to simulate Coloured Petri Net models. We run genetic algorithms three times, and each time we get new data. The goal of running genetic algorithms is to obtain the lowest LOS values with an appropriate number of Human Resources.

Table 3. Simulation results for the proposed models

	Benchmark model	First simulation model	Second simulation model	Third simulation model
Waiting time for a nursing consultation	76.5	79.5	52.2	55.8
Waiting time for a medical consultation	62.8	69.3	42.4	42.5
Waiting time for a specialist consultation	79.5	30.5	85.3	85.5
Waiting time for additional tests	59	36.7	27.4	37
Nursing consultation	16.3	17.0	15.6	15.1
Medical consultation	14.0	13.5	13.6	13.9
Specialist consultation	17.9	16.2	17.1	14.8
Additional tests	12.5	14.0	13.4	14.5
LOS	344.3	281.5	267.8	279.9
DTDT	78.5	82.4	57.5	59.7

Tables 4, 5, and 6 represent the results obtained by running genetic algorithms. The first four columns of Tables 4, 5, and 6 are the number of human resources obtained, the fifth column represents the

Table 4. First execution of the GA algorithm

Nurse	General Practi- tioner	Specialist Practi- tioner	Addi- tional tests	Min Los
1.5e+00	1.1e+00	2.7e+00	2.2e+00	1.5e+02
1.5e+00	1.2e+00	2.8e+00	2.1e+00	1.53+02
1.5e+00	1.3e+00	2.6e+00	2.2e+00	1.77+02
1.5e+00	1.4e+00	2.9e+00	2.3e+00	1.52e+02
1.5e+00	1.2e+00	2.6e+00	2.4e+00	1.51e+02
1.5e+00	1.1e+00	2.8e+00	2.3e+00	1.53e+02

Table 5. Second execution of the GA algorithm

Nurse	General Practi- tioner	Specialist Practi- tioner	Addi- tional tests	Min Los
1.6e+00	1.3e+00	1.0e+00	1.8e+00	1.9e+02
2.5e+00	2.3e+00	3.6e+00	1.6e+00	1.3e+02
2.1e+00	1.8e+00	1.0e+00	2.9e+00	1.8e+02
2.1e+00	1.8e+00	1.00e+00	3.0e+00	1.5e+02
2.1e+00	1.8e+00	1.00e+00	3.0e+00	1.8e+02
2.1e+00	1.8e+00	1.1e+00	3.0e+00	1.5e+02

Table 6. Third execution of the GA algorithm

Nurse	General Practi- tioner	Specialist Practi- tioner	Addi- tional tests	Min Los
1.8e+00	2.1e+00	1.5e+00	1.6e+00	1.5e+02
1.8e+00	2.1e+00	1.5e+00	1.6e+00	1.3e+02
1.2e+00	1.5e+00	1.4e+00	1.5e+00	1.9e+02
1.6e+00	2.1e+00	1.4e+00	1.7e+00	1.6e+02
1.6e+00	2.1e+00	1.3e+00	1.6e+00	1.9e+02
1.8e+00	2.1e+00	1.5e+00	1.6e+00	1.4e+02

calculated objective function. At the beginning, we pointed out that in the Benchmark model, each stage of the ED contains only one person, for example, one doctor, one nurse, etc. The first simulation model is built based on the results obtained in Table 4, while the second simulation model is built based on the results obtained in Table 5, and the third simulation model is built based on the results obtained in Table 6. Regarding the results obtained in Tables 4, 5, and 6, we take the approximate values of these results when entering them into the simulation models. We run the three models and compare the results with the benchmark model. In the second column of Table 3, we find the simulation results for the benchmark model. The third column of Table 3 shows the simulation results for the first model. The fourth column of Table 3 shows the simulation results for the second model. In the fifth column of Table 3, we find the simulation results for the third model.

Based on the results obtained in Table 3, we note that the LOS value decreased by 18.24% for the first simulation model compared to the Benchmark model. This is due to a decrease in waiting times for additional tests and specialized medical consultation, and this is due to the results obtained in Table 4. We notice in Table 4 the increase in the number of specialist doctors and radiologists. As for DTDT, we notice a slight increase, as human resources were not modified in the nursing consultation stage.

Regarding the second simulation model, we note that the LOS value decreased by 22.22% compared to the standard model. This is due to a decrease in waiting times for nursing consultation and additional tests, and this is due to the results obtained in Table 5, where we note the increase in the number of nurses and radiologists. As for DTDT, it decreased by 26.75%, due to the adjustment that occurred in the nursing consultation stage.

Regarding the third simulation model, we note that the LOS value decreased by 18.7% compared to the benchmark model, due to a decrease in waiting times in most stages; this is due to the results obtained in Table 6, where we note the increase in the number of general doctors, nurses, and radiologists. As for DTDT, it decreased by 23.94%, due to the adjustment in the number of human resources in each stage.

5 Conclusion

There have been many researches in the field of healthcare in recent years, especially in emergency departments. To determine resources in the emergency department, this study presented an approach based on modeling and optimization. The emergency department was modeled using a Coloured Petri Net, which is an effective tool widely used for systems modeling complex. Genetic algorithms are run several times in order to determine the appropriate amount of resources, each time new solutions are obtained. This study gave good results, through which several models are proposed, in each case both LOS and DTDT are reduced. This approach allows decision-makers in emergency departments to quickly find appropriate solutions, as this approach allows suggesting several models, which helps decision-makers to choose the appropriate model. In this study, we focused on one goal, which is to reduce LOS and DTDT. In future studies, we will add other objectives in order to improve the quality of service in emergency departments.

References

[1] S. Nas and M. Koyuncu, "Emergency Department Capacity Planning: A Recurrent Neural Network and Simulation Approach," *Computational and Mathematical Methods in Medicine*, vol. 2019, pp. 1–13, Nov. 2019, DOI: 10.1155/2019/4359719.

[2] O. Derni, F. Boufera, and M. F. Khelfi, "An Advanced Heuristic Approach for the Optimization of Patient Flow in Hospital Emergency Department," *International Journal of Intelligent Systems and Applications*, vol. 11, no. 9, pp. 29–39, Sep. 2019, DOI: 10.5815/ijisa.2019.09.04.

[3] M. Yousefi and R. P. M. Ferreira, "An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department," *Brazilian Journal of Medical and Biological Research*, vol. 50, no. 5, 2017, DOI: 10.1590/1414-431x20175955.

[4] M. Yousefi, M. Yousefi, R. P. M. Ferreira, J. H. Kim, and F. S. Fogliatto, "Chaotic genetic algorithm and Adaboost ensemble metamodeling approach for optimum resource planning in emergency departments," *Artificial Intelligence in Medicine*, vol. 84, pp. 23–33, Jan. 2018, DOI: 10.1016/j.artmed.2017.10.002.

[5] A.F. Najmuddin, I.M. Ibrahim, and S.R. Ismail, "A Simulation Approach: Improving Patient Waiting Time for Multiphase Patient Flow of Obstetrics and Gynecology Department (O&G Department) in Local Specialist Centre," *WSEAS Transactions on Mathematics*, vol. 9, n. 10, pp. 778–790, 2010.

[6] B. J. Buckley, E. M. Castillo, J. P. Killeen, D. A. Guss, and T. C. Chan, "Impact of an Express Admit Unit on Emergency Department Length of Stay," *The Journal of Emergency Medicine*, vol. 39, no. 5, pp. 669–673, Nov. 2010, DOI: 10.1016/j.jemermed.2008.11.022.

[7] J. YEH and W. LIN, "Using simulation technique and genetic algorithm to improve the quality care of a hospital emergency department," *Expert Systems with Applications*, vol. 32, no. 4, pp. 1073–1083, May 2007, DOI: 10.1016/j.eswa.2006.02.017.

[8] M. Zeinalnezhad, A. G. Chofreh, F. A. Goni, J. J. Klemeš, and E. Sari, "Simulation and Improvement of Patients' Workflow in Heart Clinics during COVID-19 Pandemic Using Timed Coloured Petri Nets," *International Journal of Environmental Research and Public Health*, vol. 17, no. 22, Article No. 8577, Nov. 2020, DOI: 10.3390/ijerph17228577.

[9] K. Salimifard, S.Y. Hosseini, and M.S. Moradi, "Improving Emergency Department Processes Using Coloured Petri Nets," in *CEUR Workshop Proceedings, Vol. 989*, pp. 335–349, 2013.

[10] J. Jihene, A. El Mhamedi, and H. Chabchoub, "Simulationmodel of Emergency Department," in *2007 International Conference on Service Systems and Service Management*, Jun. 2007, DOI: 10.1109/icsssm.2007.4280152.

[11] *Applications and Theory of Petri Nets* (Lecture Notes in Computer Science, vol. 5606), G. Franceschinis and K. Wolf, Eds. Berlin, Heidelberg: Springer, 2009.

[12] N. Hamza, M. A. Majid, and F. Hujainah, "SIM-PFED: A Simulation-Based Decision Making Model of Patient Flow for Improving Patient Throughput Time in Emergency Department," *IEEE Access*, vol. 9, pp. 103419–103439, 2021, DOI: 10.1109/access.2021.3098625.

[13] M. Laskowski, B. C. P. Demianyk, J. Witt, S. N. Mukhi, M. R. Friesen, and R. D. McLeod, "Agent-Based Modeling of the Spread of Influenza-Like Illness in an Emergency Department: A Simulation Study," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 6, pp. 877–889, Nov. 2011, DOI: 10.1109/titb.2011.2163414.

[14] J. Wang, J. Li, K. Tussey, and K. Ross, "Reducing Length of Stay in Emergency Department: A Simulation Study at a Community Hospital," *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, vol. 42, no. 6, pp. 1314–1322, Nov. 2012, DOI: 10.1109/tsmca.2012.2210204.

[15] R. Konrad et al., "Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study," *Operations Research for Health Care*, vol. 2, no. 4, pp. 66–74, Dec. 2013, DOI: 10.1016/j.orhc.2013.04.001.

[16] S. Ceschia and A. Schaerf, "Modeling and solving the dynamic patient admission scheduling problem under uncertainty," *Artificial Intelligence in Medicine*, vol. 56, no. 3, pp. 199–205, Nov. 2012, DOI: 10.1016/j.artmed.2012.09.001.

[17] S. Ceschia and A. Schaerf, "Dynamic patient admission scheduling with operating room constraints, flexible horizons, and patient delays," *Journal of Scheduling*, vol. 19, no. 4, pp. 377–389, Nov. 2014, DOI 10.1007/s10951-014-0407-8.

[18] P. Demeester, W. Souffriau, P. De Causmaecker, and G. Vanden Berghe, "A hybrid tabu search algorithm for automatically assigning patients to beds," *Artificial Intelligence in Medicine*, vol. 48, no. 1, pp. 61–70, Jan. 2010, DOI: 10.1016/j.artmed.2009.09.001.

[19] C. Kittipittayakorn and K.-C. Ying, "Using the Integration of Discrete Event and Agent-Based Simulation to Enhance Outpatient Service Quality in an Orthopedic Department," *Journal of Healthcare Engineering*, vol. 2016, pp. 1–8, 2016, DOI: 10.1155/2016/4189206.

[20] [20] M. Gül and A. F. Guneri, " A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system," *International Journal of Industrial Engineering – theory Applications and Practice*, vol. 19, 2012.

[21] M. Lamiri, F. Grimaud, and X. Xie, "Optimization methods for a stochastic surgery planning problem," *International Journal of Production Economics*, vol. 120, no. 2, pp. 400–410, Aug. 2009, DOI: 10.1016/j.ijpe.2008.11.021.

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