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AN APPROACH BASED ON COLOURED PETRI NET AND NSGA-II TO IMPROVE THE EMERGENCY DEPARTMENT

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Abstract. Health care sector faces major challenges in light of the appearance of new diseases. The emergency department (ED) is an important area in the hospital, where it plays a major role in the presence of these challenges. The 'ED' is a complex system due to the random flow of patients and the complex nature of its resources. In this paper, the authors model and simulate the 'ED' by means of coloured Petri nets, and to determine the appropriate amount of resources, the NSGA-II algorithm is developed. After determining the appropriate amount of resources through the NSGA-II algorithm, the simulation model of the current system is modified with the amount of new resources obtained through the NSGA-II algorithm. The results are compared between the current system and the obtained system. This study was conducted in Hassani Abdelkader Hospital, located in the city of Sidi Bel Abbes, in western Algeria.

Keywords: Emergency department, simulation, optimization, coloured Petri net, NSGA-II

1 INTRODUCTION

The Emergency Department (ED) is an important component of the entire health-care system. It is one of the most crowded departments that bears greater pressure loads in comparing with other components of the healthcare system. The demand for emergency services has increased exponentially in recent years requiring a high degree of coordination and interrelations between human and material elements [1].

Long waiting time is a common problem for Emergency Department (ED). Optimization of patients' flow and bottleneck elimination in the ED could provide a solution that decreases cost and enhances the quality of care [2]. The 'ED' has become the focus of many researchers, due to the main task it performs in the hospital. Most of the researchers focused on accommodate unscheduled arrivals, competing priorities and heterogeneous patient care needs, waiting time reduction and material, and human resources allocation. The emergency department is a dynamic and complex system, which makes it difficult to analyze the behavior of the system, and not to rely on analytical models [3]. Therefore, emergency department managers require timely and accurate tools to optimize resource utility in a complex and ever-changing patient care process [4].

There are several techniques for analyzing dynamic and complex systems of health care. Although modeling approaches have been standardized as methods to evaluate health care, these approaches are not sufficient for analyzing complex health care delivery systems. The dynamic simulation modeling introduces several advantages with recent advances in computing power and data analytics. In healthcare system, it has been used generally to solve bottlenecks related to healthcare in general [5, 6]. Different researches depending on the staffing levels and internal processes were studied using simulation model to improve the emergency department performance. Particulary, the simulation modeling make it possible to simulate the impact of system on health care delivery without costly direct experimentation. It provides a great service for decision-makers in the emergency department to review, analyze and evaluate the behavior of the system, in order to reduce waiting time, improve patient flow, and optimize the use of human and material resources [7, 8, 9].

The main purpose of this paper is to introduce a new simulation model based on colored Petri nets, in order to accurately study the behavior and vulnerabilities of the emergency department system and to more efficiently investigate the patient flow in the Emergency Department (ED), and reduce waiting times. Petri nets have been a popular formalism for modeling systems exhibiting behaviors of competition and concurrency for almost a half century [6]. Colored Petri nets, an extension to regular Petri nets, are a powerful tool for system performance evaluation [10, 11].

The ED is organized into different areas, each area contains several treatment spaces with a setup suited to different patient needs. Some areas have highly specialized equipment for monitoring and advanced life support, while other areas have a simpler setup used for low complexity care. In this context, we use a Non dominated Sorting Genetic Algorithm (NSGA-II) to determine the appropriate resources that helps us greatly in the improvement processes. After determining the number of added resources, we rerun the simulation and compare the obtained results with the standard model. This paper is organized as follows. Section 2 reviews the literature related to this problem. In Section 3, the hospital in which the study was conducted is described. In Section 4 the description of the patient flow chart is presented. The proposed approach and computational study are reported in

Section 5 and the paper finishes with concluding remarks and futures solutions in Section 6.

2 LITERATURE REVIEW

'ED' in recent years drawn the attention of many researchers being an important component of the health industry, most of them focused on different aspects in order to provide a tool to help decision-makers improve the efficiency and effectiveness of these departments [12]. Most of the studies related to EDs are about improving service quality decreasing patient waiting time and study of the complexity of 'ED' based on computer models [7]. The application of simulations is not new in the health industry [13], many researchers have focused on solving the problem of overcrowding in 'ED' using simulation techniques [1, 14].

Nas and Koyuncu [15] developed several ML algorithms to predict patient arrival rates, depending on the characteristics associated with patients coming to the emergency department. These predictions were used as an input parameter in a simulation model developed, and through the simulation results, bottlenecks in the 'ED' were determined. To reduce the waiting time, both Ala and Chen [16] proposed mathematical models and algorithmic frameworks, and to solve the problem of patient scheduling, the Tabu search method and L-shaped algorithm were relied on. An agent-based model developed by Yousefi and Ferreira (2017) [7], in which the process of allocating resources is done based on the observations of a staff agent in their respective sections. Six different scenarios are proposed, in each scenario, the different KPIs are compared and verified.

To determine the amount of resources required in the 'ED', Derni et al. [17] relied on the technique of fuzzy logic, the system was modeled using colored Petri Net in order to verify the optimization results, the patient's stay in the 'ED' was significantly reduced. To address the problem of overcrowding, Yousefi et al. [18] relied on agent-based simulation approaches, genetic algorithms, and machine learning. The aim of this study is to modify the material and human resources, taking into account some of the restrictions imposed by the management of the 'ED'. The field of research in the healthcare system is very broad, as Ceschia and Schaerf [19] tackled the problem of patient admission scheduling by devising a metaheuristic approach based on simulated annealing and a complex neighborhood structure. This method is able to accept a large number of patients in a reasonable time (up to 4 000 patients).

Simulation is an effective method in the discrete event system, Gul and Guneri [20] built a simulation model of a university hospital with a capacity of 40 000 patients per year, aiming to optimize the use of available resources, changes were made during working hours with an increase in the number of nurses and doctors in the evening shift. This change provided a significant improvement by 30 % in the average length of patient stay. The decision-making process in the 'ED' is very sensitive. To solve this problem, Nunes et al. [21] presented a decision model to control the acceptance process, a Markov decision process was applied, a hypothetical prototype was created using the value iteration algorithm. Through this model, the admission control process is carried out in the 'ED' in order to maintain the optimal consumption of resources. The 'ED'is a complex system, and the Markov decision process in it is rather difficult. Bappy and Rahman [22] relied on the Analytical Hierarchy Process (AHP), a technique used to organize and analyze complex decisions. A simulation model was built to improve patient flow in the emergency department, after several scenarios were proposed; the optimal scenario was reached by the Analytical Hierarchy Process (AHP) technique.

3 THE EMERGENCY DEPARTMENT OF HASSANI ABDELKADER

The University Hospital Hassani Abdelkader in the city of Sidi Bel Abbes is one of the most important hospitals in the Algerian West. The hospital's emergency department receives about 3 000 patients per month, with an average of 100 patients per day. The 'ED' of Hassani Abdelkader Hospital contains several departments: pediatrics, orthopedics, suturing, and emergency rooms (surgical and clinical) in addition to other departments. The medical staff consists of 8 resuscitators, 10 surgeons, 20 general practitioners, and 20 residents, in addition to 16 nurses and receptionists.

4 PATIENT FLOW CHART

Patient flow management is one of the most essential elements to improve the quality of services in the 'ED'. A good patient flow leads to a reduction in waiting time and patient length of stay [23]. A long waiting period is a major obstacle to providing high-quality service and may lead to wasted time and customer dissatisfaction [24]. Recently, modeling and simulation have been relied heavily on to solve several problems in the emergency department [25, 26]. The Unified Modeling Language (UML) cannot be relied on, because real-world information is fundamentally uncertain [27]. To address the problem of waiting time and patient length of stay, a hierarchical CP-Nets model is proposed. To better monitor the behavior of the system, an executable version of the system has to be provided [27, 28]. The executable version helps to check and monitor the final behavior of the system before it is executed [29]. Figure 1 shows the path that the patient follows when he comes to the emergency department. After the triage process, critically ill patients are transferred directly to the surgery room. If the operation is successful, they are transferred to the resuscitation room for 24 hours and then transferred to another department according to the patient's condition. For patients with a non-critical condition, the patient is directed according to his condition, some patients need a nursing consultation, and the majority of patients are directed to a general practitioner. The general practitioner examines the patient, then directs him to either a specialist practitioner or a nurse. In the end, the patient leaves the emergency department, according to the medical report, or is directed to another department.

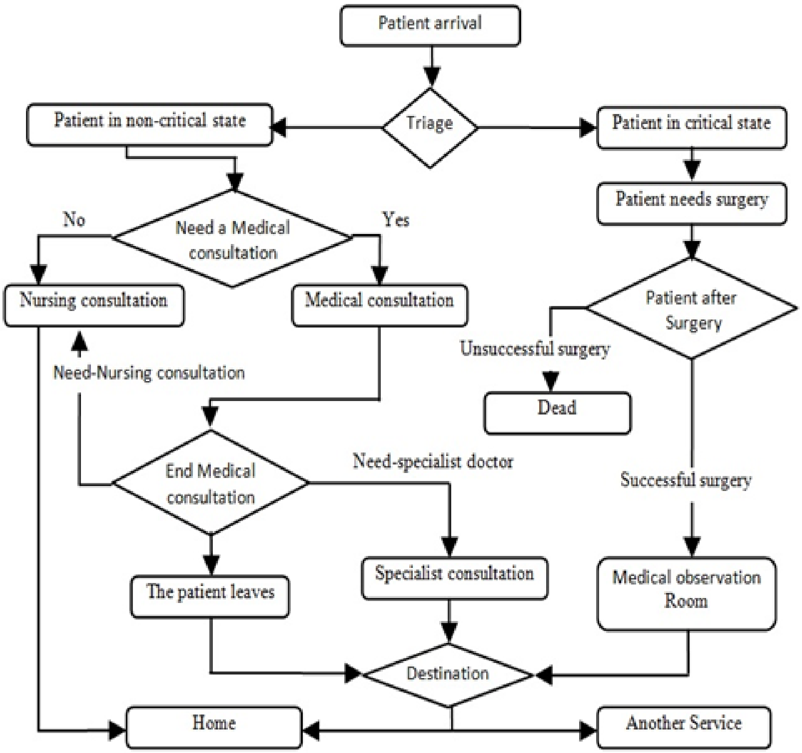

Figure 1. Flow chart of patients in the ED

5 THE PROPOSED APPROACH

In this section, the proposed approach is explained, after the definition of the KPIs, a mathematical model is proposed and a simulation model is created by means of a colored Petri net. Then, how to employ the NSGA-II algorithm in optimization will be discussed.

5.1 KPIs of Emergency Departments

Key performance indicators (KPIs) provide important information to 'ED' decision-makers to set goals, monitor implementation results, and support action plans. KPIs allow decision makers to identify critical points and problems that can be solved by optimizing time and resources [30]. Among the most important key performance indicators are the following:

- The patient total length of stay (LOS): The time a patient spends in the emergency department.

- The Door to Doctor Time (DTDT): The amount of time between a patient's arrival and the first medical consultation.

These indicators have been relied on in many studies [31, 32].

5.2 ED Mathematical Model

In this study, we will try to present a mathematical model to solve the problem of the length of the patient's stay in the 'ED' and reduce waiting times. We will start by introducing some definitions that facilitate the mathematical expression of the problem. After that, we know the decision variables that are used in the proposed algorithm. An objective function is established through which we determine the relationship between the available resources and the length of time the patient spends in the emergency department.

5.2.1 Parameters

- N: Number of patients;
- i: Index of a patient; $i = 1, 2, \ldots, N$;
- $P[i]$: A table containing the time each patient spends at the resource R_r;
- R: Resources available to the patient (triage, medical consultation, nursing consultation ...), for example: $R[r] = R[1] = 3$ means we have 3 nurses.
- r: Index of a Resource; $i = 1, 2, \ldots, N$; ($r = 1$ (triage), $r = 2$ (medical consultation), ...).
- D_r: The amount of time patient P_i spends in resource R_i.
- D_i: The amount of time patient P_i spends on the R_i resource, including waiting time ($D_{i+1} = D_i + D_r$).
- S: Total time periods for all patients relative to resource R_r ($S = \mathrm{SOME}(D_i)$).
- M_r: The average length of stay for a patient in the resource R_r ($M_r = S/i$).

5.2.2 The Proposed ALS_Rr Algorithm

Algorithm ALS_Rr
Input: R_r, D_r
Output: M_r (average length of stay for a patient in resource R_r)

- $D_i = 0$; $S = 0$;
- $i = 0$; $k = 0$; $j = 0$;
- $N = 50$;
- For $i = 1$: (N divide R_r)
- $D_i = D_i + D_r$

- For $k = 1$: R_r
- $P[i] = D_i$
- $i = i + 1$
- END
- END
- if N mod $R_r \neq 0$
- $D_i = D_i + D_r$
- END IF
- For $k = 1$: $(N \bmod R_r)$
- $P[i] = D_i$
- $i = i + 1$
- END
- For $j = 1$: N
- $S = S + P[j]$
- END
- $M_r = S/N$

Output the M_r.

5.2.3 Objective Function

Many researchers in the field of health care, especially in the emergency department, have worked to reduce the length of the patient's stay while taking into account the cost in terms of material and human terms. For this purpose, we worked on defining two objective functions:

1. The first objective function serves to reduce the patient's length of stay

$$Min\ frd = \sum_{r=1}^{R} ALS\_Rr(Rr, Dr). \tag{1}$$

2. The second objective function works to reduce the number of human resources while ensuring the quality of service

$$Min\ fRs = \sum_{r=1}^{R} Rr. \tag{2}$$

5.3 ED Simulation Model

Simulation models are effective tools for modeling and optimizing processes in healthcare and complex systems, such as emergency departments [33, 34, 35]. Thus, simulation models are the appropriate solution to address problems in ED, with limited resources and random patient access [33, 35].

Several simulation models of the 'ED' have been created to ensure the quality of services over 24 hours, and the optimum identification of material and human resources, in order to ensure patient satisfaction and provide effective treatment services [16, 20, 21].

In this study, coloured Petri net was used to model the emergency department system. Petri nets give a clear graphical presentation of the system and a mathematical approach. Petri nets demonstrate communication and control patterns and information flow [27]. After studying all the stages and operations that take place at the emergency department level, a model of the system was created, with the help of the expertise of the medical and administrative staff.

Figure 2 represents the simulation model for the 'ED'. This model includes the basic operations from reception, triage, a medical consultation, and surgical operations until the patient leaves the 'ED'. In the model, we find all the places where the patient can be, the patient moves from one place to another according to the state in which he is. We show in Table 1 the places and in Table 2 the transitions of the simulation model.

Each place of the model is marked by the PATIENT colour set, which is a CPN Tools record, the latter includes many important attributes that we need to calculate waiting times, duration of operations in various stages, the total length of stay, and other characteristics. In Table 3 we show the functions attached to the transitions, among which we find the exponential distribution function with a mean of 8.0 that is used to model the arrival of the patient to the ED. Figure 3 shows the subpage of the additional tests.

5.4 NSGA-II Algorithm

NSGA is a type of multi-objective optimization genetic algorithm, which is based on Pareto optimization. The NSGA is based on a non-dominant stratification method so that the better individuals have a greater chance of being selected for the next generation. The fitness sharing method enables individuals in the critical layer to distribute equally, overcomes the over-reproduction of super individuals, and prevents premature convergence [36]. But the implementation of the NSGA algorithm reveals the following shortcomings:

- The time complexity of non-dominated sorting is very high.
- The shared parameters need to be assigned artificially, which will have a significant impact on population diversity.
- The elite strategy is not supported.

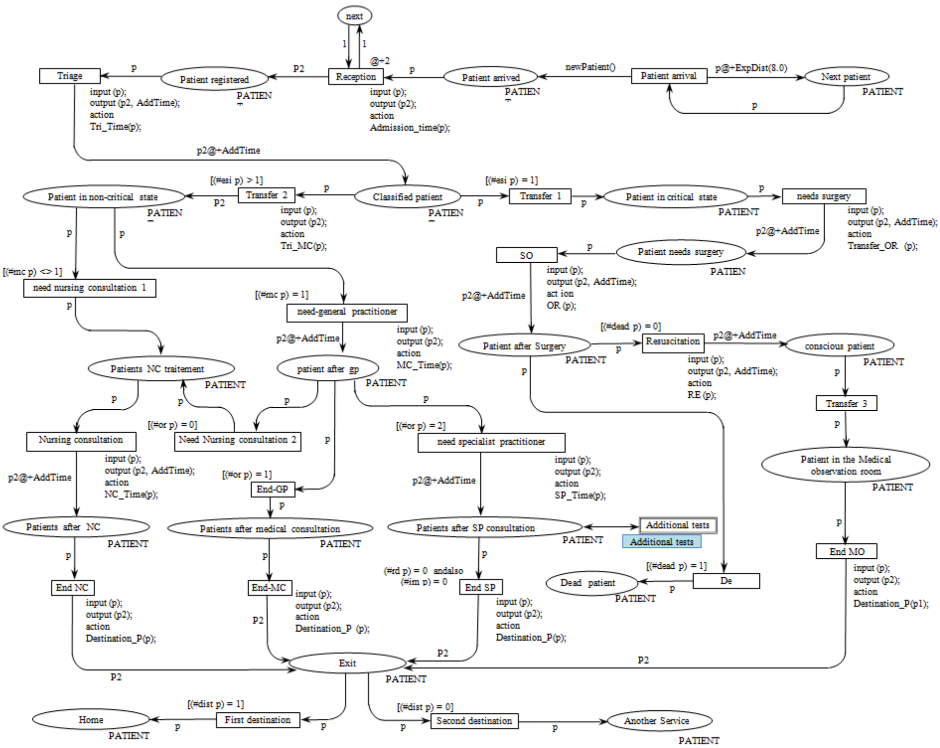

Figure 2. Main page of ED simulation model using coloured Petri net

To overcome the previously mentioned shortcomings, The NSGA-II algorithm is developed, which is a fast non dominated sorting algorithm that reduces the time complexity of the sorting algorithm. The elite strategy and crowding distance algorithm are applied to change the shared function algorithm in NSGA so that the performance of variety maintenance is no longer dependent on the assigned shared parameters.

5.4.1 Resource Identification Using the NSGA-II Algorithm

The resources in the emergency department vary according to the need and the period of time the patient spends in each stage. In the case studied, the most important resources that the patient may pass through are:

- Nursing consultation: the time spent by the patient in this stage is between 10 and 20 minutes.
- General Practitioner: the time spent by the patient in this stage is between 10 and 15 minutes.

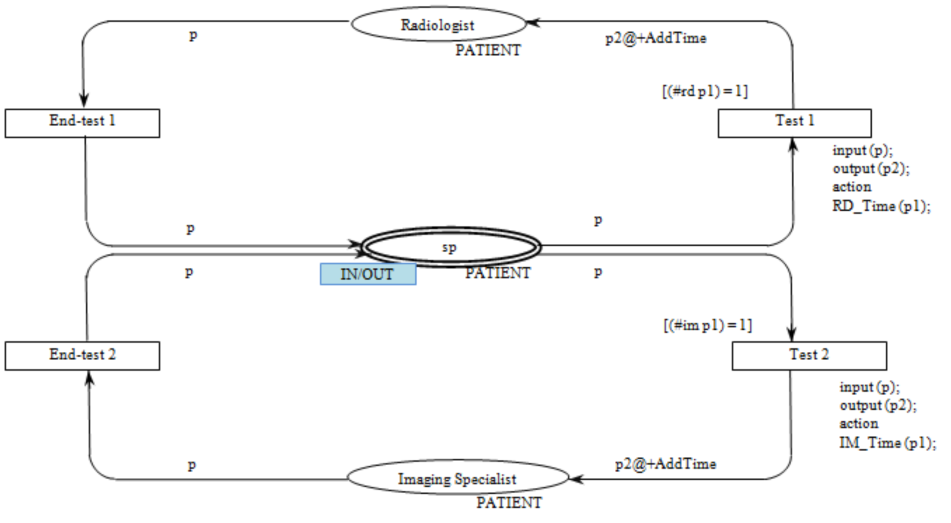

Figure 3. Additional tests page of substitution transition Additional tests in ED simulation model

- Specialist Practitioner: the time spent by the patient in this stage is between 10 and 20 minutes.
- Radiologist (Additional tests): the time spent by the patient in this stage is between 10 and 15 minutes.

In the modified NSGA-II algorithms, the maximum and minimum values are entered for each resource. Each variable x in the algorithms represents the number of resources available at each stage, for example $x = 2$ in the nursing consultation stage means we have two nurses. The time period the patient spends in each resource for each stage is entered into the algorithm. We modify the NSGA-II algorithm, where we use in the objective function the proposed ALS-Rr algorithm in order to calculate the average time spent by the patient in each resource.

5.4.2 Computational Flow

Figure 4 shows the computational flow of NSGA-II,

Step 1: A random parent population of size N is generated.

Step 2: The population is classified based on the non-domination. Each population is allocated a rank equal to its non-domination level or front number (one is the better level, two is the next better level, and so on). The crowding distance (CD) of the population at each non-dominant level is calculated, and the population is sorted in descending order of crowding distance (CD).

Place	Description
Patient arrived	The arrival of the patient at the ED
Patient registered	Patients admitted to the ED
Classified patient	A patient is classified into two cases (critical and non-critical)
Patient in non-critical state	Patient in a non-critical state (ESI $>$ 1)
Patient in critical state	Patient is in critical state (ESI $=$ 1)
Patient needs surgery	Patient in the operating room
Patient after Surgery	Patient in recovery room
Dead patient	Dead patient
Conscious patient	Successful surgery
Patient in the Medical observation room	The patient remains in the medical observation room for 24 hours
Patients NC traitement	The patient needs a nursing consultation
patient after gp	The end of the medical consultation the patient is directed to another consultation or leaving the emergency department
Patients after SP consultation	End of specialized medical consultation
Patients after medical consultation	End of medical consultation
Patients after NC	End of nursing consultation
Radiologist	The patient undergoes a radiological diagnosis
Imaging Specialist	The patient is undergoing diagnostic imaging

Table 1. Places description of the ED simulation model

Step 3: Two individuals are randomly selected. Their front number and CD are compared. Select the best and copy it to the mating pool.

Step 4: The Simulated Binary Crossover (SBX) and polynomial mutation have been applied to create offspring population of size N.

Step 5: The parent population and the child population are combined.

Step 6: The collective population is sorted by non-domination and crowding distance (CD). Since all parent and offspring population members are included, elitism is ensured.

Step 7: The process can be stopped after a constant number of iterations. If the criterion is not satisfied then the procedure is repeated from Step 3 after creating the new population from the parent population.

5.5 Simulation Results and Discussion

The aim of this study is to work on reducing LOS and DTDT, after creating the simulation model by means of a colored Petri net, we run the simulation, and we get

Transition	Description
Patient arrival	Admission of the patient to the emergency department
Reception	patient reception process
Triage	triage process
Transfer 1	Transfer for critical state
Transfer 2	Transfer for non-critical state
needs surgery	Transfer the patient to the operating room
SO	surgical operation
Resuscitation	surgical operation
De	resuscitation process
Transfer 3	Transfer the patient to the medical observation room
End CS	Patient leaving the medical observation room
need-general practitioner	Medical consultation process by a general practitioner
need Nursing consultation 1	The process of nursing consultation by the nurse after the triage process
end-GP	End of medical consultation(for the general practitioner)
need specialist practitioner	Medical consultation process by a specialist practitioner
Additional tests	Additional tests at the request of the specialist practitioner
End SP	End of medical consultation(for the specialist practitioner)
End-MC	End of medical consultation
End NC	End of nursing consultation
Need Nursing consultation 2	The process of nursing consultation by the nurse after consulting a general practitioner
Nursing consultation	Nursing consultation process
first destination	The patient leaves the emergency department and goes home
Second destination	The patient leaves the emergency department for another section of the hospital
Nursing consultation	Nursing consultation process

Table 2. Transitions description of the ED simulation model

the initial results. Then we execute the modified NSGA-II algorithm several times, and each time we get new results. The goal of the modified NSGA-II algorithm is to get the lowest LOS values with the right amount of resources. Tables 5, 6 and 7 show the results obtained. The first four columns of each table represent the number of resources allocated, and the fifth and sixth columns represent the first and second objective functions, respectively. After obtaining the appropriate amount of resources, we modify the simulation model by entering the resources obtained during the implementation process of the modified NSGA-II algorithm. Table 4 shows the simulation results. The second column of Table 4 represents the simulation results for the Benchmark Model using a colored Petri net. The third column of Table 4 represents the simulation results of the colored Petri net model, using the resources

Function	Description
ExpDist	Modeling patient access to ED
Admission_time	Calculation of the time the patient spends in the reception
Tri_Time	Calculation of the time the patient spends during the triage process
Tri_MC	A function that classifies the patient (a patient who needs medical consultation, a patient who needs nursing consultation)
Transfer_OR	Calculation of the time the patient spends in the operating room
OR	A function classifies the patient (successful operation of the patient, dead patient)
RE	Calculation of the time the patient spends in the operating room
SP_Time	Calculating the time the patient spends at the specialist practitioner
MC_Time	Calculating the time the patient spends at the general practitioner
NC_Time	Calculating the time the patient spends with the nurse
Destination_P	A function that categorizes the patient according to the destination (leaving the emergency department, another department of the hospital)
NC_Time	Calculating the time the patient spends with the nurse

Table 3. Description of the most important functions used in the ED simulation model

	Benchmark model	Simulation-first model	Simulation-second model	Simulation-third model
Waiting time for a nursing consultation	63.5	65.5	37.2	39.8
Waiting time for a medical consultation	51.8	57.3	29.4	28.5
Waiting time for a specialist consultation	70.5	20.5	74.3	73.5
Waiting time for additional tests	59	30.7	20.4	29
nursing consultation	16.5	17.2	15.8	15.3
medical consultation	14.1	13.6	13.7	14
Specialist consultation	18.1	16.4	17.3	15
Additional tests	12.8	14.3	13.7	14.8
LOS	306.3	239.5	221.8	229.9
DTDT	67.5	70.4	44.5	45.7

Table 4. Simulation results for the proposed models

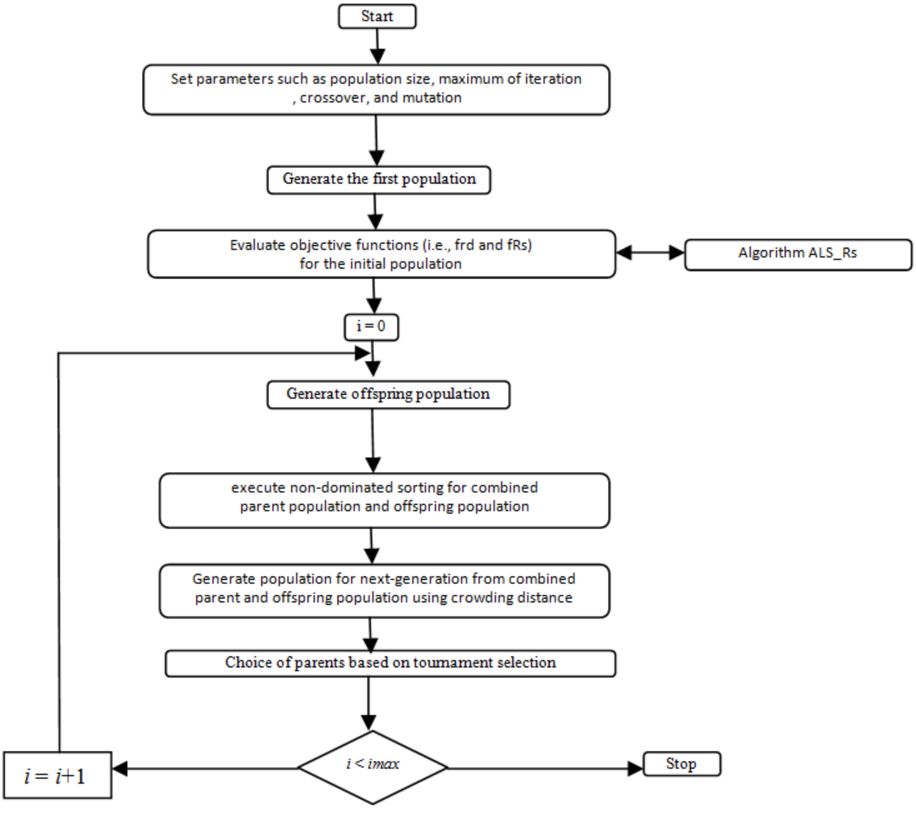

Figure 4. The computational flow of NSGA-II

obtained in Table 5. The fourth column of Table 4 represents the simulation results of the colored Petri net model, using the resources obtained in Table 6. The fifth column of Table 4 represents the simulation results of the colored Petri net model, using the resources obtained in Table 7.

X1 (Nurse)	X2 (General Practitioner)	X3 (Specialist Practitioner)	X1 (radiologist)	*frd*	*fRs*
1.53E+00	1.09E+00	2.74E+00	2.04E+00	1.49E+02	7.39E+00
1.50E+00	1.07E+00	2.74E+00	2.04E+00	1.53E+02	7.36E+00
1.51E+00	1.01E+00	2.72E+00	2.02E+00	1.77E+02	7.26E+00
1.52E+00	1.09E+00	2.74E+00	2.04E+00	1.52E+02	7.39E+00
1.52E+00	1.24E+00	2.72E+00	2.30E+00	1.51E+02	7.78E+00
1.59E+00	1.10E+00	2.74E+00	2.03E+00	1.53E+02	7.45E+00

Table 5. First execution of the modified NSGA-II algorithm

X1 (Nurse)	X2 (General Practitioner)	X3 (Specialist Practitioner)	X1 (radiologist)	*frd*	*fRs*
1.64E+00	1.32E+00	1.03E+00	1.72E+00	1.87E+02	5.71E+00
2.46E+00	2.31E+00	3.59E+00	1.63E+00	1.27E+02	1.00E+01
2.08E+00	1.83E+00	1.00E+00	2.91E+00	1.77E+02	7.82E+00
2.08E+00	1.83E+00	1.00E+00	2.97E+00	1.45E+02	7.88E+00
2.08E+00	1.83E+00	1.00E+00	2.91E+00	1.81E+02	7.82E+00
2.01E+00	1.83E+00	1.14E+00	2.92E+00	1.48E+02	7.90E+00

Table 6. Second execution of the modified NSGA-II algorithm

X1 (Nurse)	X2 (General Practitioner)	X3 (Specialist Practitioner)	X1 (radiologist)	*frd*	*fRs*
1.80E+00	2.14E+00	1.48E+00	1.62E+00	1.51E+02	7.03E+00
1.78E+00	2.14E+00	1.50E+00	1.62E+00	1.35E+02	7.05E+00
1.17E+00	1.51E+00	1.44E+00	1.51E+00	1.90E+02	5.64E+00
1.64E+00	2.13E+00	1.37E+00	1.65E+00	1.63E+02	6.79E+00
1.63E+00	2.13E+00	1.30E+00	1.64E+00	1.86E+02	6.71E+00
1.83E+00	2.14E+00	1.50E+00	1.61E+00	1.41E+02	7.08E+00

Table 7. Third execution of the modified NSGA-II algorithm

We note from the results obtained in Table 4 that the LOS value decreased by 21.81 % for the first simulation model compared to the Benchmark model, while a slight increase for the DTDT and this is logical as the resources were not adjusted for the nursing consultation. As for the second simulation model, the LOS decreased by 27.59 % compared to the standard model, and the DTDT decreased by 34.1%. As for the third simulation model, LOS decreased by 24.94 % compared to the standard model, and DTDT decreased by 32.3 %.The variables that lead to different results in the three simulation models are the waiting times for each of the nursing consultations, general and special medical consultations, and additional tests. These variables change according to the number of resources added. As for the duration of operations in the different stages, it changes slightly in the three models.

6 CONCLUSIONS AND FUTURE WORK

With the emergence of new diseases in recent years, identifying resources in emergency departments has become very difficult. This study suggested an approach based on simulation and genetic algorithms developed. The behavior of the system has been thoroughly studied, so that the emergency department is modeled using a colored Petri net, which is an effective tool for modeling complex systems. A prototype is created, then the NSGA-II algorithm is run for several times, each time giving different solutions, each time we get the right amount of resources. Simulation models were built based on the solutions obtained through the NSGA-II algorithm. This proposed approach gave good results, each time reducing LOS and

DTDT, with the difference in the amount of proposed resources. This approach allows decision-makers in emergency departments to take the appropriate decision, as it gives many and convergent solutions. In the upcoming studies, we are developing an algorithm to accurately calculate LOS and DTDT. So that it facilitates the process of employing multi-objective algorithms such as NSGA-II.

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