Optimizing Human Resource Allocation in Emergency Departments: A Combined R-NSGA-III and Colored Petri Nets Approach

Abstract. Recently, severe overcrowding in the emergency department has exacerbated the challenges faced by both patients and staff. This overcrowding leads to the patient's long stay in the emergency department as well as the financial losses of the hospital. Emergency department are vital in society, where the patient comes to it at any time, and without a prior date. The emergency department is a complex system due to the nature of the available resources in addition to unpredictable cases. Recently, many researchers have focused on reducing the time patients spend in the ED to alleviate pressure on medical staff and improve the quality of services offered to patients. In this paper, we propose an approach that combines R-NSGA-III algorithms with colored Petri nets. The emergency department is modeled using colored Petri nets, and initial results are obtained after running the simulation model. R-NSGA-III algorithms are relied on to obtain the optimal number of human resources, so that the simulation model is modified with its restarting each time and compares the results with the various proposed models. This approach helps the hospital decision-makers to find effective solutions, especially in terms of human resources.

Keywords: Emergency department; Colored Petri Net; simulation; R-NSGA-III; optimization.

1 Introduction

Emergency departments(EDs) are the basis of urgent health care, however overcrowding is a real problem that negatively affects both patients and employees[1]. However, the overcrowding of emergency departments, caused by increased patients, extends waiting times, delayed treatment and deteriorating care quality[2][3].

This issue remains a global challenge[4]persisting despite variations in national healthcare policies[5]. Prior research has highlighted the heavy workload in major hospitals, emphasizing the multifaceted nature of operational errors[6], the negative impact of long wait times on patient experience, and the declining availability of beds coupled with a rise in emergency department visits[7].

This problem is difficult due to the intricate nature of system operations and the wide range of patient clinical profiles[8]. The high volume of emergency department (ED) visits reflects a diverse spectrum of medical needs, from patients requiring basic care to those with severe conditions demanding urgent intervention. This occurs within a context of limited resources, often compounded by cost constraints [9].

The unlimited increase in material and human resources leads to huge losses for the hospital, although it solves the problem of overcrowding in the emergency department. In addition, the demand for the emergency department varies from time to time. Sometimes it reaches its maximum peak, and sometimes the demand for the emergency department decreases, and thus the various resources are not used appropriately [10].

This paper presents a hybrid approach to modeling using colored Petri nets, and to determine the appropriate human resources we use the R-NSGA-III algorithm, the aim of this approach is to find the appropriate amount of human resources taking into account the length of stay of the patient in the emergency department, thus reducing the overcrowding in the emergency department without costing the hospital financial losses while maintaining the quality of services provided to patients.

This proposed method assists hospital medical and administrative staff in optimizing human resource management, thereby improving the quality of patient care and reducing length of stay (LOS).

The remainder of this paper is structured as follows: Section 2 reviews related work in this area. Section 3 details the proposed approach. Finally, Section 4 presents our conclusions and suggests directions for future research.

2 Literature Review

Emergency departments (EDs), as a critical component of the healthcare system, have been the focus of extensive research aimed at providing tools to assist hospital managers in enhancing their efficiency and effectiveness [11]. Studies on EDs primarily focus on improving service quality through quality management concepts, reducing patient wait times, and analyzing ED complexity using computer models, multi-criteria decision-making models, and optimization methods [12].

Among the studies conducted in this context is a study conducted by Yousefi [13], in which he used the agent-based technique and simulation. Through this study, several improvement scenarios are proposed, the purpose of which is to reduce the length of the patient's stay in the emergency department. For the good use of human resources in the emergency department, Gül [14] presented a study based on simulation of discrete events. Most of the operations at the emergency department level were modeled, with improvement scenarios proposed in order to reach the optimal scenario with the optimal use of human resources. Improving patient flow depends on the good use of human resources, for this purpose Hamza [15] presented a hybrid approach based on agent-based simulation and multi-attribute decision making technique. Real data was used to compare with the results of simulation models. The techniques used for optimal planning of human resources in emergency department vary. For example, Yousefi [16] used an approach based on a chaotic genetic algorithm, through which human resources are modified, calculating the length of stay of the patient in each modification, and comparing the results with different scenarios. Another technique used by Derni [17] was using fuzzy logic. Through this approach, he worked to find a way to determine the number of human resources while ensuring the quality of services provided to patients.

Modeling and simulation are considered one of the best techniques to optimize resources in the emergency department, for this purpose Nas [18] proposed a hybrid approach that uses recurrent neural network and simulation,the aim of this approach is to determine the capacity of the emergency department for patients in order to prepare for any emergency. Simulation has been used in many researches for improvement processes in the emergency department,such as Derni [19], where he relied on colored Petri nets, where many improvement scenarios were proposed and implemented using colored Petri Nets,in order to reach the optimal scenario.

3 The Proposed Approach

This paper employs the following research methodology: a detailed workflow study of the Emergency Department (ED) was conducted to identify bottlenecks and areas of prolonged patient wait times. Key performance indicators (KPIs) used in this study include Door-to-Doctor Time (DTDT) and Length of Stay (LOS). The necessary data for system modeling and simulation were collected. A Coloured Petri Net (CPN) model was developed using CPN Tools, a powerful software suite for modeling and simulating discrete event systems designed with CPNs. In order to propose optimization scenarios, it is necessary to modify the human resources in the simulation model. For this purpose, we use the multi-objective R-NSGA-III algorithm. The goal of the latter is to find the lowest value of LOS with the appropriate number of human resources. In the R-NSGA-III algorithm, we need to propose a mathematical model, which we will explain below.

3.1 ED mathematical model

The aim of this research is to determine the human resources needed in the emergency department to optimally care for patients. And thus reduce the length of stay of the patient in the emergency department. In the mathematical model, we need parameters to be used in the proposed algorithms. An objective function is defined to determine the relationship between the available resources and the time the patient spends in the emergency department. After determining the resources, the simulation model is modified and run and the results are compared with the benchmark model.

3.1.1 The Parameters

Through Table 1, we note all the parameters that we relied on in the proposed algorithm, with an explanation.

Table 1. Parameters used in the proposed algorithm.

Parameter	Description
N	Number of patients
pt	pt = 1, 2,…, N; Index of a patient;
TM[pt]	A table showing the duration of each patient's visit to resource Rr.
RC	Resources available to the patient (Triage, medical consultation, nursing consultation …), for example: RC[r] =RC[1]=2 means we have 2 nurses.
r	Index of a Resource(r=1(Triage), r=2(medical consultation),…).
Dr	The duration of patient TMpt stay at resource RCr.
Dpt	The total duration of Patient TMpt presence at resource RCi, inclusive of any waiting period.(Dpt+1= Dpt+Dr).
TT	The total time spent by all patients at resource.RCr(TT=SOME (Dpt)).
Mr	The average length of stay for a patient in the resource RCr (Mr=TT/pt).

3.1.2 The proposed Patient_Phase_Duration algorithm

The Patient_Phase_Duration algorithm calculates the average amount of time a patient spends in a particular stage. The algorithm takes two inputs: the time spent by the patient on each resource (Dr) and the number of resources in each stage of the ED (RCr).
For instance, in a medical consultation, the waiting time for patient I+1 is the waiting time for patient I plus the duration of the medical consultation. The average time spent in the consultation phase is the average waiting time for all patients during this phase. The same principle applies to the other stages.

Algorithm Patient_Phase_Duration

- Input :RCr,Dr
- For pt = 1: (N divide RCr)
- Dpt = Dpt +Dr
- For pt = 1: RCr
- TM[pt]= Dpt
- pt=pt+1
- END
- END

- if P mod RCr ≠ 0
- Dpt = Dpt +Dr
- END IF
- For k = 1: (N mod RCr)
- TM[pt]= Dpt
- pt=pt+1
- END
- For j = 1: N
- TT = TT+ TM[j]
- END
- Mr = TT/N
- Output the Mr
-
- Output :Mr (average length of stay for a patient in resource RCr)

3.1.3 Objective function

Many researchers focus on various objectives to improve the emergency department, with most of these goals aimed at reducing the duration of patients' hospital stays. In this study, the following objective function was proposed:

$$Min\ LOS = \sum_{r=1}^{RC} \mathbf{Patient\_Phase\_Duration}(\mathrm{RC[r]}, \mathrm{D[r]})$$

The goal of the objective function is to determine the minimum value of LOS, given the appropriate Human Resources.
We add another objective function to the mathematical model, which is as follows:

$$Min\ fRs\ = \sum_{r=1}^{RC} \mathrm{R[r]}$$

3.2 ED simulation model

The simulation tool is an essential resource as it plays a significant role in monitoring system performance and improving operations in emergency departments [20]. Therefore, creating a simulation model for the ED can help in proposing and evaluating different scenarios [21]. Simulation models have been widely used in various studies to represent operations within Eds . In this research, an ED model was created using a colored Petri net, a tool frequently used to model complex and concurrent processes [22].

In this study, a simulation model was developed with the help of administrative and medical staff, following a comprehensive analysis of the various operations in the ED. Figure 1 presents the simulation model, which captures all key stages of triage, reception, and medical consultation. The model also allows for tracking all possible pathways a patient may take.

In the proposed simulation model, places are defined by the PATIENT color set, which includes attributes used to calculate operation durations at different stages, as well as waiting times and the total length of stay. The model also demonstrates the functions of the transitions. To construct and simulate the proposed ED model, CPN Tools a powerful software designed for building and simulating CPN models is used. Figure 1 shows the homepage of the ED simulation model using a colored Petri net.

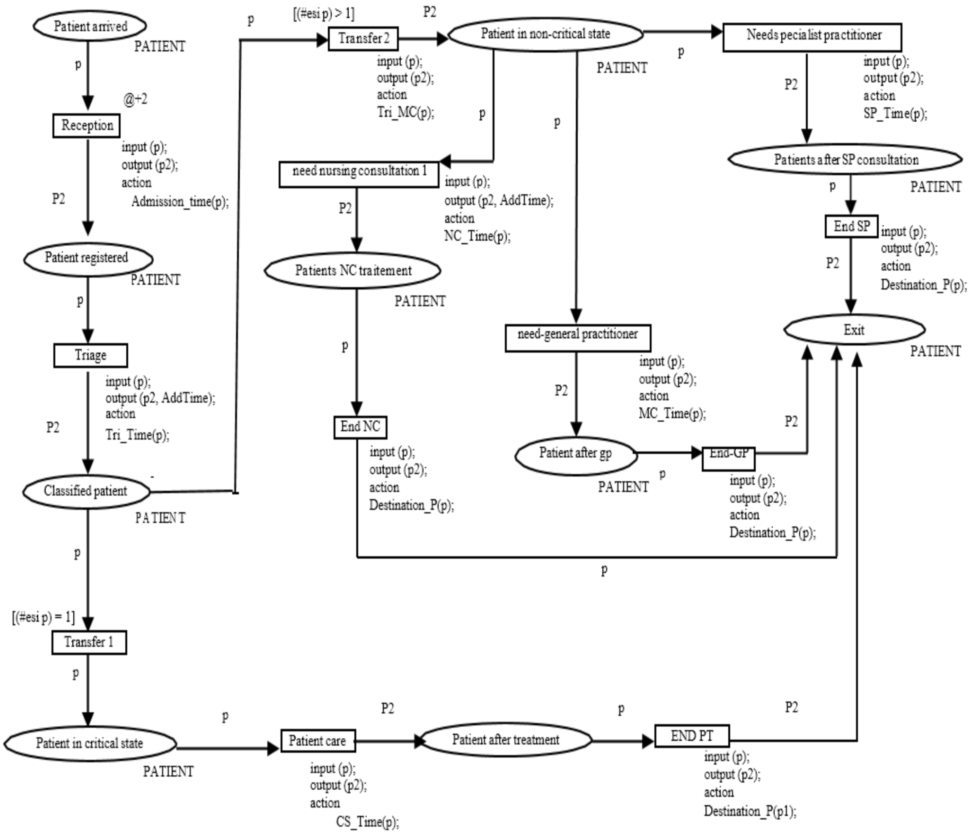

Fig. 1. ED simulation model.

3.3 R-NSGA-III algorithm

Definition: The R-NSGA-III algorithm is an improvement on the popular NSGA-III (Non-dominated Sorting Genetic Algorithm III) algorithm used to solve multi-objective optimization problems. Multi-objective algorithms aim to find optimal solutions for multiple objectives at the same time, which may be conflicting or cannot all be optimized at the same time[23].

NSGA-III began as part of the development of multi-objective genetic algorithms, and it works on classifying non-dominated solutions across multiple levels with a mechanism for choosing between these solutions [24].

R-NSGA-III is an improvement or modification of the NSGA-III algorithm that aims to enhance the ability to deal with large multi-objective problems that require variance enhancement or efficient response in dealing with changing environments. This modification focuses on enhancing rapid response or iterative improvement in cases where the multiplicity of objectives is asymmetric or when some objectives are more important than others [25].

3.4 Determine resources using the R-NSGA-III algorithm

Effective resource management in the Emergency Department (ED) is essential. As a result, numerous researchers have focused on optimizing resource utilization to enhance service quality and patient satisfaction. Due to these constraints, the ED must become more efficient and adaptable.

In this study, we will utilize the R-NSGA-III algorithm to determine the optimal number of resources in the ED. R-NSGA-III is specifically designed to address problems with a large number of objectives, making it suitable for real-world applications such as engineering, logistics, and machine learning. R-NSGA-III is a powerful tool for multi-objective optimization, especially in complex problems where balancing and exploring trade-offs between numerous competing objectives is required. Given the characteristics of R-NSGA-III, it allows us to efficiently identify the appropriate number of resources needed in the ED.

In this study, we will focus on key resources, such as nursing consultation (10 to 20 minutes), general practitioner (10 to 15 minutes), specialist practitioner (10 to 20 minutes), and radiologist (10 to 15 minutes). The use of these resources in the Emergency Department (ED) is based on the specific needs of patients and the amount of time they spend with each resource.

In the R-NSGA-III algorithm, minimum and maximum values are defined for each resource, along with the time allocated to each. Each variable x in the algorithm represents the number of human resources available at each stage. For example, x=4 in the medical consultation stage means there are four doctors available at this stage. We modify the R-NSGA-III algorithm by integrating the proposed Patient_Phase_Duration algorithm into the objective function to calculate the average time a patient spends at each resource.

3.5 Simulation Results and Discussion:

The objective of this study is to reduce waiting times, thus shortening the patient's length of stay (LOS) in the Emergency Department (ED), which is a crucial factor in improving service quality. After developing the simulation model based on the colored Petri net, preliminary results are obtained by running the initial simulation model. Then, the modified R-NSGA-III algorithm is executed three times, with each run yielding different results. The goal of the R-NSGA-III algorithm is to minimize LOS while ensuring an adequate number of human resources.
Table III presents the results obtained. The first four columns of Table III show the number of human resources identified, while the fifth and sixth columns correspond to the first and second objective functions. After determining the number of human resources, these values were integrated into the simulation model, leading to the creation of three modified simulation models. Table II presents the simulation results for each of these three models, as well as for the standard model. The second column of Table II displays the simulation results for the standard model using the colored Petri net. The third column shows the simulation results for the colored Petri net model with the resources from the first row of Table III. The fourth column presents the simulation results using the resources from the second row of Table III. Finally, the fifth column of Table II presents the simulation results for the resources from the third row of Table III.

Table 2. SIMULATION RESULTS FOR THE FOUR MODELS.

	Benchmark model	Simulation-first model	Simulation-second model	Simulation-third model
Waiting time for a nursing consultation	64.3	67.2	38.2	38.8
Waiting time for a medical consultation	52.8	56.4	28.3	27.5
Waiting time for a specialist consultation	71.5	22.5	75.3	72.5
Waiting time for additional tests	60	32.6	22.3	28
nursing consultation	16,7	17.1	15,9	15,4
medical consultation	14.7	13.5	13.5	14,4
Specialist consultation	18.4	16.4	17.2	15,3
LOS	316.4	249.7	231.8	228.9
DTDT	65.5	68.3	42.4	43.6

The results presented in Table II indicate that the LOS value decreased by 17.85% for the first simulation model compared to the standard model, while there was a slight increase in DTDT. In the second simulation model, the LOS decreased by 23.38%, and the DTDT reduced by 34.22%. For the third simulation model, the LOS decreased by 24.40%, and the DTDT decreased by 32.44%. The duration of operations remained almost unchanged across all simulation models. The primary difference lies in the waiting times, which have a direct impact on the patient's length of stay in the ED. Waiting times vary between simulation models based on the resources available.

Table 2. Results of executing the r-nsga-iii algorithm

X1 (Nurse)	X2 (General Practi-tioner)	X3 (Specialist Prac-titioner)	X1 (radiologist)	LOS	fRs
1.5	1.07	2.85	2.02	1.55e+02	7.4 e+00
2.	1.92	1.00	2.81	1.96e+02	7.82e+00
1.88	2.14	1.47	1.74	1.51e+02	7.03e+00

4 Conclusions And Future Work

Emergency departments are increasingly facing chal-lenges such as overcrowding and limited resources. In many countries, overcrowding in emergency rooms is a significant issue, resulting in problems for both patients and staff, including longer wait times, extended stays, and medical errors. One of the key challenges for decision-makers is efficiently allocating human resources to manage the unpredictable patient influx at various times. This study introduces a novel approach based on simulation using Colored Petri Nets and the R-NSGA-III algorithm. A thorough analysis of the various operations at the emergency department level was conducted, and a prototype simulation model was developed as a benchmark. The R-NSGA-III algorithm was used to optimize human resources by calculating the Length of Stay (LOS). Based on the R-NSGA-III results, three distinct simulation models were created, each with its own resource allocation. Simulations were run for all three models, and the results were compared to the benchmark model. This approach aids in determining optimal human resources for managing the random flow of patients, thereby reducing both LOS and DTDT. The main challenge remains accurately calculating LOS and DTDT to enable the effective use of optimization algorithms.

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