Improving Emergency Department Operations: A MOPSO and Colored Petri Nets Approach to Resource Allocation

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Abstract

Recently, the emergency department (ED) has been experiencing overcrowding, which causes numerous problems for both patients and employees. This situation leads to an increased length of stay in the ED for arrivals, as well as financial losses for the hospital. Emergency services play a crucial role in society, as people require them at any time without a prior appointment. The ED is a not-simple due to the diversity of resources available and the unpredictable nature of emergencies. Recently, many researchers have focused on shortening the length of patient stays in the emergency department in order to reduce the pressure on medical staff and improve the quality of medical services provided. In this paper, we propose a new method based on a multi-objective algorithm, such as multi-objective particle swarm optimization (MOPSO), and colored Petri nets. The emergency department is modeled using colored Petri nets. After running the simulation model, initial results are obtained. In order to modify human resource counts within the simulation model, MOPSO algorithms are used. This approach helps hospital decision-makers identify optimal solutions for managing human resources in the emergency department.

Keywords: Emergency Services Efficiency; Colored Petri Net; Human Resource Optimization; simulation; MOPSO.

DOI: https://doi.org/10.36548/jitdw.2025.2.005
Received: 24.04.2025. received in revised form: 27.05.2025, accepted: 14.06.2025, published: 27.06.2025

1. Introduction

Emergency services are important, and anyone may resort to these services at any time and stage in their life. The ED faces many difficulties in order to achieve the levels of performance required for patients. Waiting times, in addition to the length of time that the patient spends in the ED, are some of the main indicators that many researchers rely on to evaluate the quality of services [1]. Currently, the demand for ED services is increasing, and therefore, ED management has become more important. One of the most significant difficulties that the medical staff faces is fully caring for the patients who come to the ED daily, as it requires the use of an appropriate amount of resources, especially human resources, which are often very limited, in addition to good coordination between these resources [2]. The ED is not simple, due to the dynamism and diversity of health care provided in it, as well as the random flow of patients [3]. Overcrowding is a common problem in EDs, the main cause of which is often a lack of material and human resources. To address these challenges, decision-makers must ensure optimal use of available resources. [4]. Some departments rely on increased medical staff, but this remains expensive, requiring the search for other solutions [5]. Simulation is used as an effective tool to improve operations within the ED, and considered an appropriate way to solve many problems in the ED [6]. This study employs Colored Petri Nets to model the emergency department and utilizes MOPSO algorithms to determine the required number of human resources. Through this study, decision-makers can optimally control human resources and thus reduce the period patients spend by reducing waiting periods. In Section 2 of this study, we list some of the research that has been conducted. In the third section, we explain in detail the proposed approach, while the last section contains conclusions and future solutions.

2. Literature Review

The health care sector receives attention in every country and has a major role in national policy [6]. In the past decades, many researchers have focused on working in the field of health care, especially in emergency departments [7]. This specialty is considered emerging in the medical field [8]. The use of simulation and optimization algorithms in the medical field is not new [9-10], especially in the emergency department [11]. Decision support in the emergency department is important for hospitals and patients [12]. In order to effectively manage the emergency department, Dotoli [13] proposed a model to describe the various operations in the ED. The continuous Petri net was used to monitor the workflow and behavior of patients from their arrival at the ED until they are discharged. To evaluate the ability to cope with emergencies when disasters occur, Li [14] proposed an approach based on fuzzy Petri nets. Models are created using fuzzy Petri nets, in order to evaluate some of the proposed scenarios. Decision-making in the ED is complex and difficult due to the work environment and time pressure. For this purpose, Pegoraro [15] proposed a hybrid model that combines the Preference Ranking Organization and the methods of the Decision-Making Experiment and Evaluation Laboratory (DEMATEL). Its goal is to improve procedures and decision-making by ED managers in order to reduce the phenomenon of overcrowding. To predict the number of Reducing the patient's length of patient coming to the ED, Vest [16] used technology based on interoperable health information, so that this data helps him take the necessary measures to confront any emergency that may occur at any moment. Reducing the patient's length of stay also results from reducing waiting times. In response to this need, Kuo [17] introduced an approach combining machine learning techniques and systems thinking principles, the purpose of which is to predict the waiting time in the ED. Optimal use of resources helps reduce crowding in the ED. As a solution, Yousefi [18] proposed a model employing a chaotic genetic algorithm in order to obtain the necessary human resources in the emergency department.

3. Proposed Work

In this section, we present the proposed approach for modeling and optimizing human resource allocation in the emergency department.

3.1 ED Mathematical Model

Reducing the length of a patient's stay requires calculating the average length of time and waiting time that the patient spends in each resource, such as, medical, nursing, and specialized consultation. Employing an optimization algorithm requires creating a mathematical model.

3.1.1 Parameters

Table 1. Key Parameters Used in the ED Model.

Parameter	Description
P	Patient Count
k	$k \in \{1, 2, ..., P\}$, where k is the patient index

T[k]	Time spent by each patient at each resource R[r]
R	The resources available (e.g., triage etc.) are represented by R[r]. For instance, R[1]=3 (3 nurses available at r=1)
r	Index of a resource with r=1 representing triage, r=2 medical consultation, and so on.
DTIMEk	The duration for which patient Tk utilizes resource Rr.
DTIMEk	The total time Patient Tk spends on resource Rr, including both usage and waiting time, where DTIMEk+1= DTIMEk+DTIMEr.
S	The total time spent by all patients on Rr, calculated as S=SOME (DTIMEk)
Mr	The average time a patient spends in resource R[r], calculated as $M_r = S / k$.
DTIMEr	The time the patient spends on each resource

3.1.2 Presentation of the MeanPatientTime_Rr Algorithm

To calculate the average length of time that a patient spends in the emergency department, the sum of the time periods for the various stages (medical, nursing, specialized consultation, additional tests) is calculated. In this study, we propose the MeanPatientTime_Rr algorithm, this algorithm calculates the average duration a patient spends across the previous stages. Two inputs are used: Rr, DTIMEr

Algorithm MeanPatientTime_Rr

- Begin
- Input :Rr,DTIMEr
- k = 1
- while (k <= (The result of dividing P by Rr)) do
- DTIMEk = DTIMEk +DTIMEr
- If(k≠1) k = k+1 END of IF
- while(k <= Rr) do
- T[k]= DTIMEk
- k++
- end
- end
- if P modulo Rr ≠ 0

- DTIMEk = DTIMEk +DTIMEr
- END of IF
- k++
- while(k <= P modulo Rr) do
- T[k]= DTIMEk
- k++
- END
- j=j+1
- while (j<= P) do
- S = T[j] + S (Calculate the sum of the periods for all patients in the resource Rr)
- END
- Output: Mr = S/P (representing the mean duration a patient spends in resource Rr)
- END

3.1.3 Objective Function Specification

Decision makers seek suitable solutions in order to improve the quality of services for patients, taking into account the financial value of human resources. In this research, we propose two objective functions: Extractive summarization identifies the top k sentences (S_k) using cosine similarity:

- The first objective function estimates the average time a patient spends in the emergency department.

$$Min\ LOS = \sum_{i=1}^{r} MeanPatientTime\_Rr(R[i], D[i])$$

- The second objective function calculates the number of human resources

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

3.2 Model of the ED

Simulation is a powerful tool that plays a key role in monitoring and enhancing emergency department operations [19]. Therefore, proposing simulation models for the ED would be very useful to evaluate various scenarios [20]. In this study, an ED model was generated, after an analytical study of the system's behavior, where the expertise of the medical staff was sought, a colored Petri net was used as a mathematical tool for modeling. Through the simulation model in Figure 1, we observe all the basic stages that the patient goes through in the ED, from the process of triage, reception, medical observation, and various other stages. The model allows us to observe all possible scenarios a patient may encounter. Places are distinguished by a patient color scheme, including attributes to calculate the duration of key operational stages, as well as waiting times and total length of stay, and it also has transition functions.

3.3 MOPSO Algorithm in brief

3.3.1 Definition

The PSO algorithm is one of the collective intelligence algorithms proposed by Kennedy and Eberhardt [21]. The PSO algorithm is based on simulating the behavior of a group of birds in collective foraging. PSO is easy to use and can be integrated with other algorithms to improve the accuracy and efficiency of the original algorithm [22]. PSO is widely used in many fields such as health [23], energy [24], and artificial intelligence [25]. PSO began to attract attention from many researchers and became the most popular soon after its introduction, but the problem remains in optimizing only one objective. For this purpose, a new concept of multi-objective PSO (MOPSO) was introduced, through which many objectives can be improved at the same time, using more than one objective function is used [26].

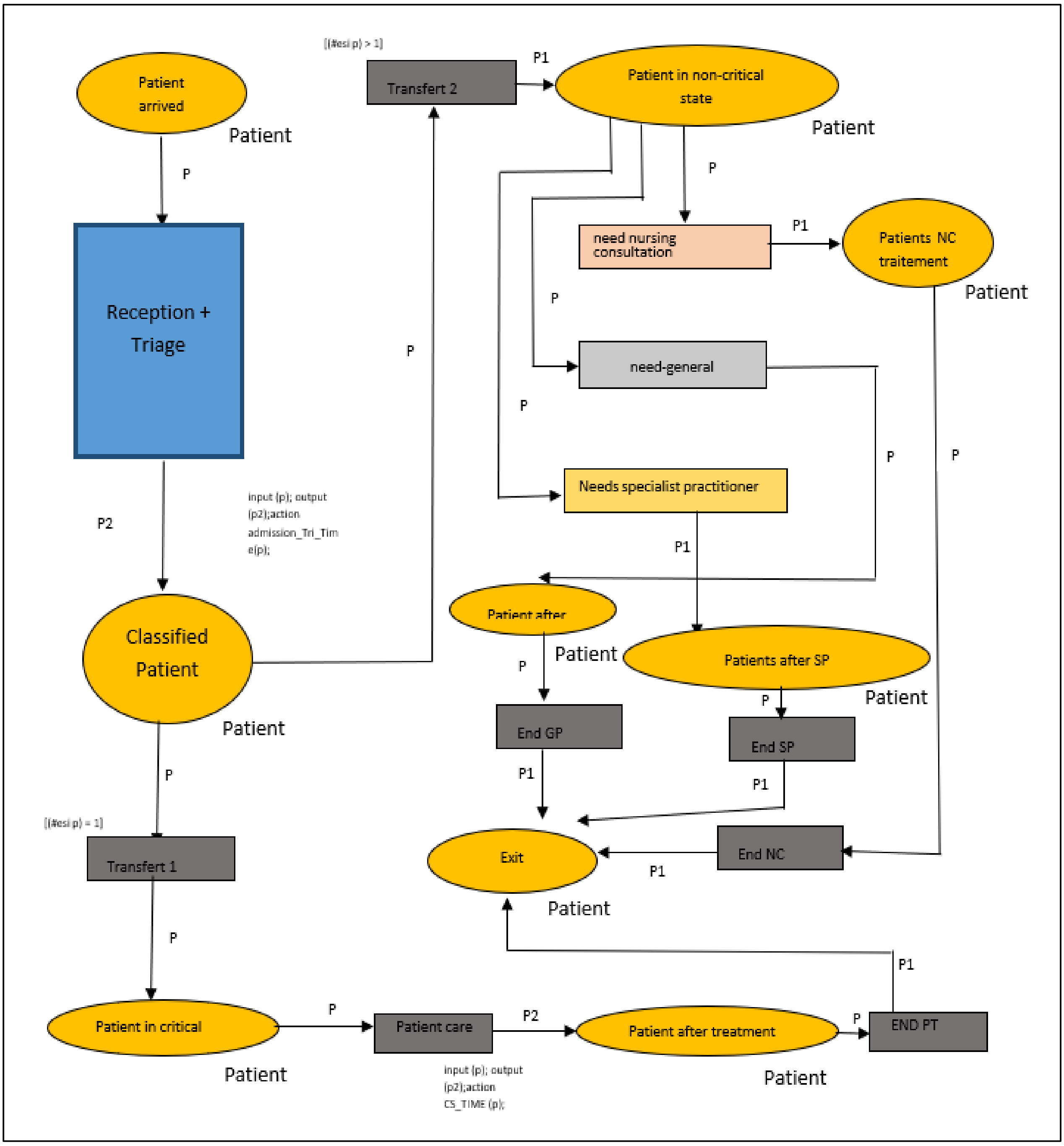

Figure 1. ED Simulation Model

3.3.2 Resource Allocation Using the MOPSO Algorithm

The resources available in the ED vary according to the cases received by the emergency department, including, doctors, specialist nurses, and other medical staff. This research concentrates on the primary resources that the majority of patients are likely to require, namely:

- General physician: The time period in this stage ranges from 10 to 15 minutes.

- The specialist doctor: The time period in this stage ranges from 10 to 20 minutes.
- Radiology specialist (additional examinations): The time period in this stage ranges from 10 to 15 minutes.
- Nursing consultation: The time period in this stage ranges from 10 to 20 minutes.

In the modified MOPSO algorithms, maximum and minimum values are defined for each of the resources mentioned earlier. Each variable x represents the number of resources allocated. For instance, having x = 3 during the medical consultation = three doctors are involved. The patient's length of stay in each resource is recorded as a primary input. We enhanced MOPSO by integrating MeanPatientTime_Rr into its objective function to estimate patients' average resource time.

3.4 Analysis and Interpretation of Simulation Results

After creating the simulation model based on the colored Petri net, we obtained preliminary results by running the initial simulation model. We then ran the modified MOPSO algorithm three times, obtaining different results each time. The goal of the MOPSO algorithm is to obtain the lowest LOS values with the appropriate number of human resources. Table 3 shows the results obtained. Columns one through four in Table 3 present the number of human resources determined, while the fifth and sixth columns represent the first and second objective functions. Once the number of human resources has been determined, we modified them in the simulation model, resulting in three simulation models. The simulation outcomes for these three models, as well as for the standard model, are summarized in Table 2. In Table 2, the second column contains the simulation outcomes of the standard model implemented with the Colored Petri net. In Table 2, the third column presents the simulation outcomes for the Colored Petri Net model, based on the resources specified in the first row of Table 3. Table 2 fourth column displays simulation results using resources from the second row of Table 3. Table 2 fifth column displays simulation results using resources from the third row of Table 3.

As shown in Table 2, the LOS value decreased by 21.08% in the first simulation model compared to the standard model, while there was a slight increase for DTDT. In the case of the second simulation model, LOS decreased by 26.73%, while DTDT experienced a reduction of 35.26%.

Table 2. Simulation Outcomes for the Four Models

	Standard model	**Model 1**	**Model 2**	**Model 3**
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

In the third simulation model, LOS was reduced by 27.65%, while DTDT saw a reduction of 33.43%. The duration of operations remains approximately constant in each simulation model. The difference is in waiting times, which affect the length of time the patient stays in the ED. Waiting times change from one simulation model to another depending on the available resources.

Table 3. Outcomes from the Execution of the MOPSO Algorithm

X1 (Number of nurses)	**X2 (Number of General Practitioner)**	**X3 (Number of Specialist Practitioner)**	**X1 (Number of radiologist)**	**LOS**	$\boldsymbol{fRs}$
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

Good management of the emergency department and appropriate use of its resources are very important to avoid overcrowding in the ED by patients. This study introduces a methodology based on the colored Petri net and the MOPSO algorithm. Following an analysis of the different processes within the emergency department, an initial model was constructed by using a Colored Petri Net, which is well-suited for modeling complex systems. The MOPSO algorithm is run repeatedly, and each execution produces a distinct allocation of human resources. According to the results derived from the latter, three new simulation models are created and run. A comparison with the standard model revealed that the proposed method led to significant improvements, consistently reducing LOS and DTDT across all simulations. This study helps decision makers in the hospital make appropriate decision, as it provides many solutions. In upcoming studies, we attempt to propose a reliable method to accurately calculate the LOS and DTDT. This facilitates the process of employing multi-objective algorithms such as MOPSO.

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