Journal of Soft Computing Paradigm (ISSN: 2582-2640)
www.irojournals.com/jscp/

Improving Patient Flow in the Emergency Rooms using Coloured Petri Nets and the ACO Algorithm

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Abstract

Overcrowding is certainly one of the major problems that have affected the work of the health care system in recent years, especially in the Emergency Department (ED), In addition, overcrowding has a significant impact on the quality of health care in hospitals. In addition to creating issues for patients and staff, overcrowding in the ED can lead to medical errors, longer wait times, and thus causes financial losses to hospitals. Emergency services are considered necessary in society, given the human need for them at any stage of their life. The emergency department is a complex system due to the nature of the resources it contains. Many researchers are interested in proposing many solutions to solve many problems in the emergency department. Researchers rely on many methods and techniques such as simulation, optimization algorithms, data mining, and other methods. In this research, we try to propose an approach based on the ant colony optimization (ACO) algorithms and colored Petri nets, the aim of which is to reduce waiting times and thus reduce the length of the patient's stay. Simulation models are built utilizing colored Petri nets, and to determine human resources, the ACO algorithms are used. This research helps the administrative staff in the emergency department find appropriate solutions for human resources.

Keywords: Emergency department; Coloured Petri Net; ACO; simulation; optimization

DOI: https://doi.org/10.36548/jscp.2024.2.003
Received: 12.04.2024, received in revised form: 01.05.2024, accepted: 12.05.2024, published: 27.05.2024

1. Introduction

The Emergency Department (ED) plays an effective role in health care, as it takes care of most patients in their various critical and non-critical conditions. Recently, increased demand on the emergency department has led to overcrowding, causing great pressure and making the medical staff's job difficult. In addition, a number of patients with non-critical conditions present themselves to the emergency department [1]. The problem of overcrowding is a major problem in the emergency department, and is due to several reasons, including the lack of human and material resources. One of the solutions that decision makers may rely on is modifying human resources, but this solution remains expensive, and other methods must be searched for with less costs [2]. Simulation is among the effective ways to improve processes within EDs and complex systems. For good resource control, a methodology is used that includes discrete event simulation and optimization algorithms. This technique is widely used in healthcare [3]. This research presents an approach based on Coloured Petri net and ACO algorithm, and the objective of this work is to model and improve the processes that occur in the ED. To determine the appropriate number of resources, ACO algorithm are relied on. Ant Colony Optimization (ACO) stands as a prominent metaheuristic inspired by the foraging behavior of ants. Its application extends across various domains, from engineering to logistics, owing to its ability to efficiently solve complex optimization problems. By harnessing the collective intelligence of artificial ants, ACO can effectively explore the solution space, potentially uncovering novel and optimal solutions that traditional methods might overlook.

Using this approach, decision makers are given several nearly ideal solutions, through which the Length of Stay (LOS) and waiting time of patients are reduced. The rest of this article is ordered as follows. In section 2, some research that have been done on ED are listed. Section 3 contains the suggested approach, and the final section summarizes the conclusion and future solutions.

2. Literature Review

The Emergency Department (ED) is the most vital component of healthcare systems, being one of the main routes of admission to a hospital [4]. The emergency department is a complex system due to several characteristics, such as the different cases, the random access of patients, in addition to the diversity of resources available within it [5].One of the most common problems that the emergency department suffers from is overcrowding. This negatively affects the quality of health care, and also leads to an increase in the death rate, delayed treatment, and patients leaving the emergency department without seeing a doctor [6]. In order to solve these problems, researchers used many techniques and methods, such as modelling, simulation, and optimization algorithms. Among the researchers who relied on simulation is Nahhas [7], who used simulation to solve the problem of emergency department overcrowding. Many discrete event simulation models were built to study the behavior of the system and determine the required resources such as the number of doctors, operating and examination rooms, assistants and nurses. Another approach proposed by Bouramtane[8] combines mathematical programming and simulation. An emergency department simulation model is designed to develop and arrange the ED in a variety of proposed scenarios that include unexpected patient flows. To address the problem of congestion in the emergency department, Weng[9] proposed a model with applications of radio-frequency identification, activity relationship diagrams, and discrete event simulation, to simulate nurse movement flows within the emergency department and determine the relationship between different treatment departments. To forecast hospital emergency department visits, Xie[10] proposed a machine learning-based approach, through which accurate prediction of patient visits to the emergency department, even moderate predicting time horizons, can be achieved through this approach improving operational efficiency and quality of care. Researchers are looking for a more accurate triage system that gives patients better priorities depending on their medical conditions because of the inconsistent triage process in emergency rooms and the limits in triage nurses' practice with triage instruments. For this purpose, Elhaj[11] presented a study in which learning techniques are applied Automation to build an automated screening model for more accurate evaluation. In another research by Kuo[12] he used machine learning to predict waiting time in emergency departments. This strategy uses machine learning algorithms to forecast individualized, real-time wait times in emergency rooms. An approach was proposed by Thiago [13], the latter based on scenarios, whereby scenarios are used to anticipate future events and variable neighbourhood research to schedule patients.

3. The Proposed Approach

3.1 ED Mathematical Model

The goal of this research is to reduce the patient's length of stay and reduce the waiting time at various basic stages. First, a mathematical model is proposed. We begin by defining the parameters used in and using them in the proposed algorithms. An objective function has been defined to determine the relationship between available resources and the time a patient ordains in the emergency department. These resources are employed in the proposed simulation models.

3.1.1 Parameters

We explain the parameters used in the mathematical model in Table 1

Table 1. Mathematical Model Parameters

Parameter	Description
P	Number of patients
pt	Index of a patient; pt = 1, 2,…, P;
TM[pt]	a table containing the time each patient spends at the 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; pt = 1, 2,…., P; (r=1(Triage), r=2(medical consultation),…).
Dr	The amount of time patient TMpt spends in resource RCi.
Dpt	The amount of time Patient TMpt spends on the RCi resource, including waiting time (Dpt+1= Dpt+Dr).
TT	Total time periods for all patients relative to 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 Mr_RCr Algorithm

The Mr_RCr algorithm calculates the average length of time a patient spends in a certain stage. The algorithm takes two inputs: the amount of time the patient spends on each resource(Dr) in addition to the number of resources in each stage of ED (RCr).

For example, in a medical consultation, the waiting period for patient I+1 is the waiting period for patient I plus the time period for the medical consultation. The average time period in the medical consultation phase is the average waiting times for all patients in this phase. The same goes for the other stages.

Algorithm Mr_RCr

- Input :RCr,Dr
- For pt = 1: (P 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: (P mod RCr)
- TM[pt]= Dpt
- pt=pt+1
- END
- For j = 1: P
- TT = TT+ TM[j]
- END
- Mr = TT/P
- Output the Mr

- Output :Mr (average length of stay for a patient in resource RCr)

Figure 1. Algorithm Mr_RCr

3.1.3. Objective Function

Many researchers focus on several goals for improvement in the emergency department, and the majority of these goals aim to shorten the duration of hospital stays for patients. In this research, the following objective function was proposed:

$$Min\ LOS = \sum_{r=1}^{RC} \mathbf{Mr\_RCr}(\mathrm{RCr}, \mathrm{Dr})$$

The objective of the objective function is to learn the minimum value of LOS, given the appropriate HR.

3.2. ED Simulation Model

The simulation tool is an effective tool that contributes significantly to monitoring system behavior and improving operations in emergency departments [14]. Therefore, creating a simulation model for ED will help to propose and evaluate different scenarios [15]. Simulation models have been used in many researches to model operations in the emergency department. In this research, an ED model is designed using a colored Petri net. The latter is widely used to model complex concurrent processes [16].

In this research, a simulation model was created using a colored Petri net, after a good study of the various operations conducted at the emergency department level, and with the assistance of the medical and administrative staff. The simulation model is shown in Figure 2. Through the model we find all the basic stages of the processes of sorting, reception and medical consultation. Through the model, we observe all the possible paths that the patient may take.

We note through the proposed simulation model that places are distinguished by the PATIENT colour set, and the latter contains attributes used to calculate the duration of operations at various stages, in addition to waiting periods and the total length of stay. We also show in the model the functions of the transitions. To build and simulate the proposed ED model we use CPN tools. CPN Tools is a powerful tool used to build and simulate CPN models. Figure 2 represents the flowchart of a patient in the emergency department, Figure 3 shows the home page of the ED simulation model using a colored Petri net, Figure 4 shows the subpages for critical state.

3.3. ACO Algorithm

The ant colony optimization (ACO) algorithm is a probabilistic mechanism for dissolve computational issue that can be diminutive to finding better track through graphs [17].

Artificial ants are examples of multi-agent systems that draw inspiration from real ant behavior. The most often used model of biological ant communication is frequently pheromone-based. [18]. Artificial ant groups have become a preferred method for many optimization tasks that many researchers rely on. The efficiency of ACO was primarily verified through the traveling vendor problem. So far, ACO has been effectively used thus far to address a number of issues, such as project scheduling and data mining [19]. ACO features its pheromone model and construction of probabilistic solutions. In addition, a local search procedure is often used to improve solutions.

Generally, an ACO resolves the problem by repeatedly performing the following steps:

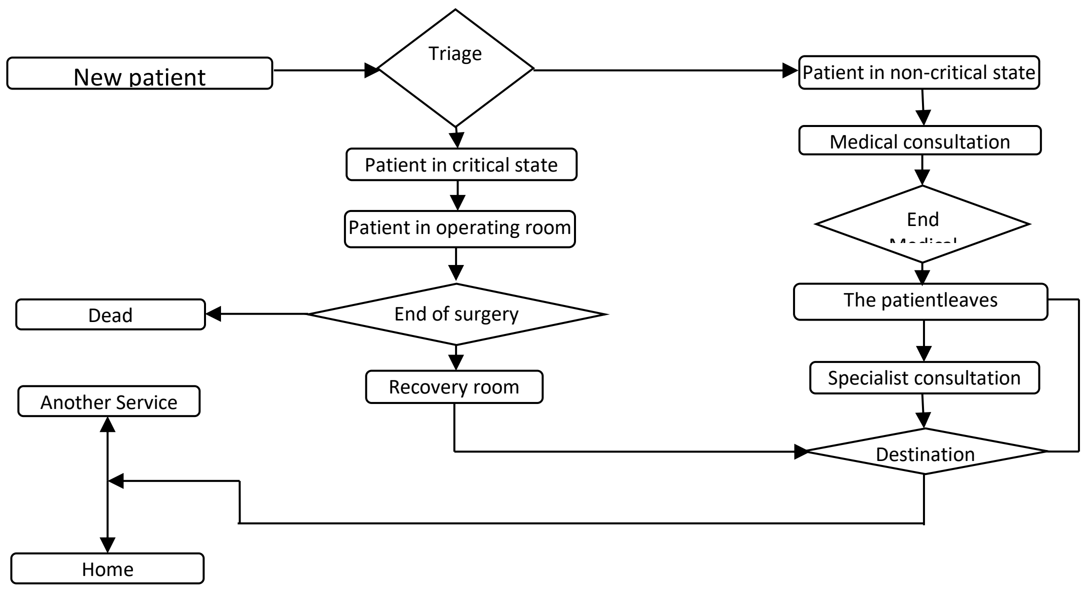

Figure 2. The Flowchart of a Patient in the Emergency Department

- Build potential solutions using pheromone values and heuristic information in accordance with a given probability distribution.

- Pheromone values should be updated with previously developed solutions in order to steer future work in the direction of the high-quality solution space.

The solution construction method and pheromone model need to be properly developed in terms of the particular problem attributes, such as decision variables and solution structures, in order to solve a given problem using ACO.

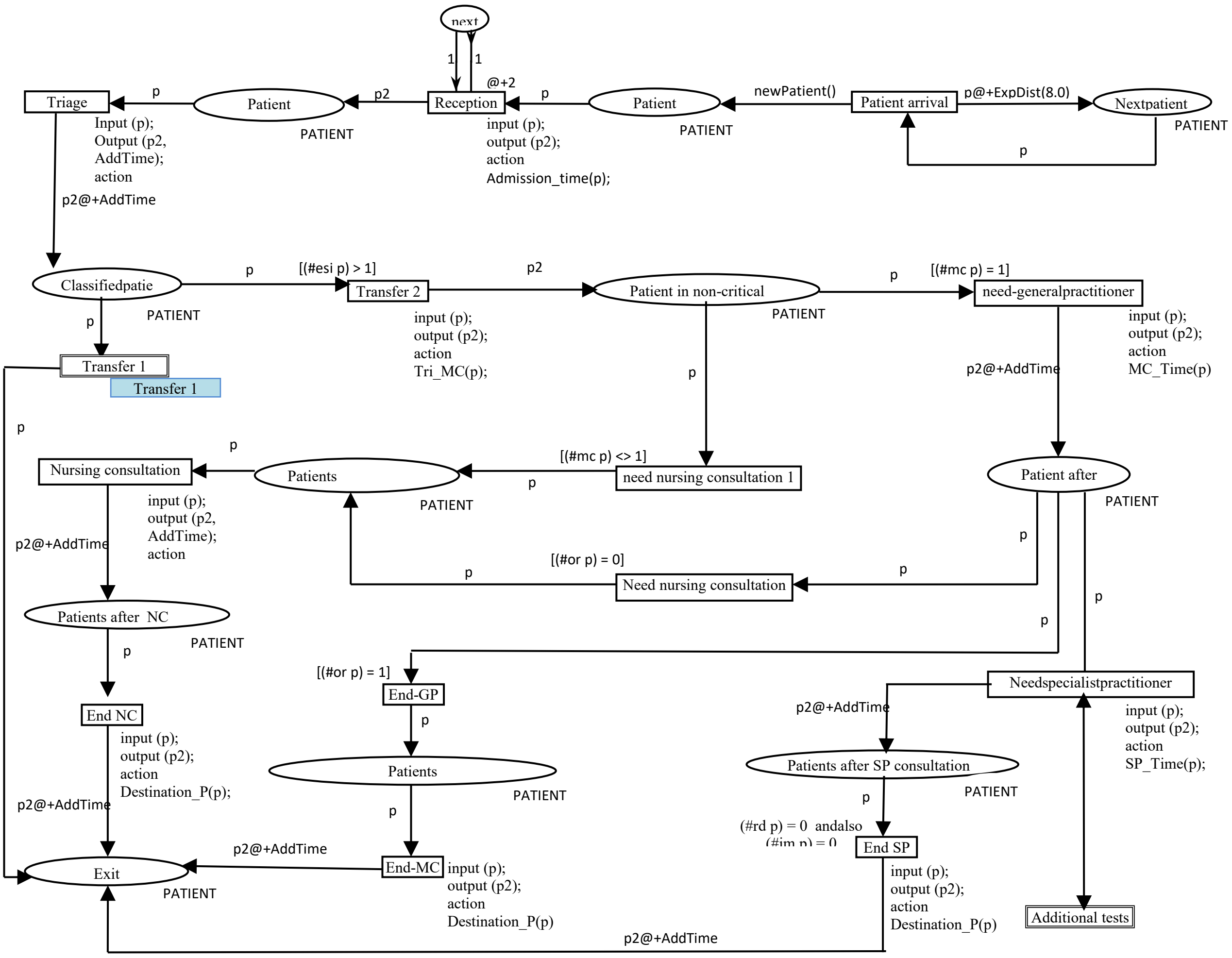

Figure 3. The ED Simulation Model's Main Page using Coloured Petri Net

3.3.2. Determine Resources using the ACO Algorithm

The management of resources in the emergency department is very important. For this purpose, many researchers have concentrated on the optimal use of resources in order to ameliorate the quality of service and patient satisfaction. With these limitations, the emergency department must be more efficient and flexible.

In this research, we will use ant algorithms to find the appropriate number of resources in the emergency department. The ants in the ACO make probabilistic decisions based on both heuristic information and pheromone levels. Based on the characteristics of the ACO, which are to explore new solution components and exploit promising regions in the solution space, we can do a quick access to find the appropriate number of resources in the emergency department.

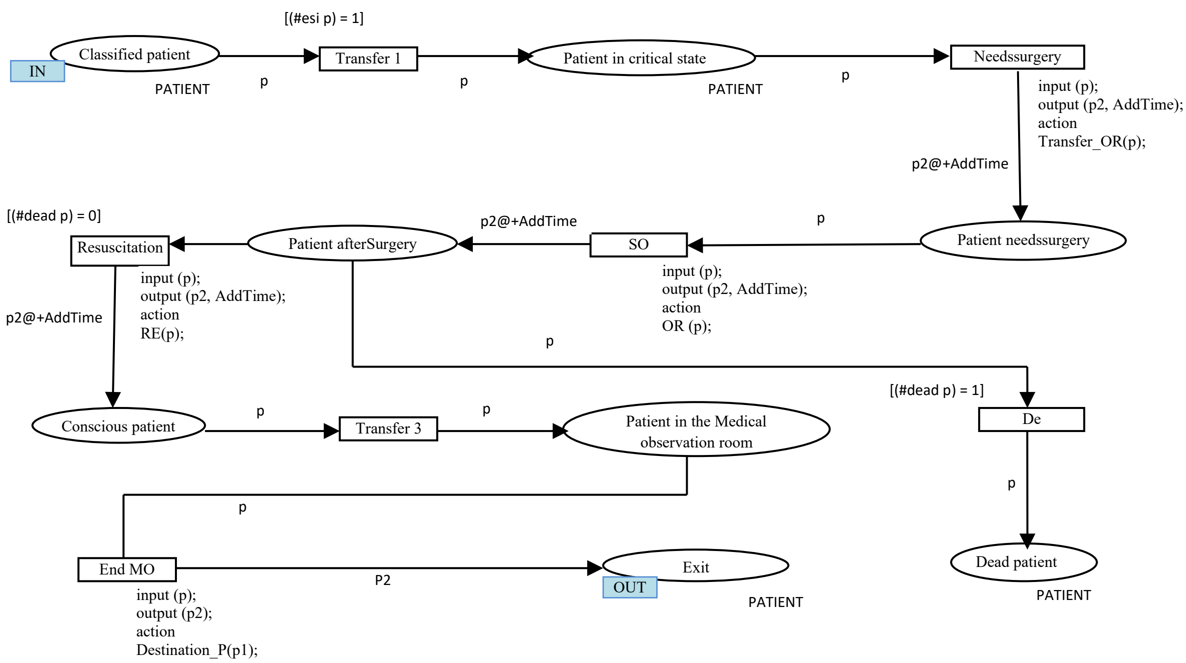

Figure 4. Subpage of the Substitution Transition for Transfer 1(Critical State).

In this research, we will focus on the important resources represented by a nursing consultation (10 to 20 minutes), a general practitioner (10 to 15 minutes), a specialist practitioner (10 to 20 minutes), and a radiologist (10 to 15 minutes). Resource use in the emergency department varies based on need and the length of time a patient spends in each resource.

In ACO algorithms, minimum and maximum values are entered for each resource, as well as the duration of time spent on that resource. Each variable x in the algorithms represents the number of human resources available at each stage. For example, x = 4 in the medical consultation stage means we have four doctors at this stage.

We modify the ACO algorithm, where in the objective function we use the proposed Mr_RCr algorithm to calculate the average time a patient spends at each resource.

3.4. Simulation Results and Discussion

The goal of this research is to reduce waiting times and length of patient stay. First, the simulation model is created and run to obtain initial results. Then the ACO algorithm is run several times, each time different results are obtained. From Table 2 we notice that the results differ each time, and in each execution process a new number of HR is obtained, with new values for LOS.

In Table 2, the first four columns represent the resources obtained by running the ACO algorithm, and the last column we find the results of the Min LOS objective function obtained. Three new simulation models are built based on the results obtained in Table 2. The first model is based on resources (the first line of Table 2), the second model is based on resources (the third line of Table 2), and the third model is based on resources (Fourth line of Table 2). Table 3 represents the results obtained by running the three models compared to the Benchmark model.

In the Benchmark model we have two people at each stage, for example in the nursing consultation stage we have two nurses. From the second table, we notice the decrease in LOS and DTDT for the three models compared to the Benchmark model.

For the first model, LOS decreased by 25.62% and DTDT decreased by 15.36% compared to the Benchmark model. As for the second model, LOS decreased by 23%, and DTDT decreased by 17.15% compared to the Benchmark model. For the third model, LOS decreased by 27.4% and DTDT decreased by 29.47% compared to the Benchmark model. The LOS and DTDT values differ from one model to another, as a result of the different waiting period values in the different stages, which greatly affects the LOS and DTDT values, due to the different resources available in each stage. The duration of operations in each stage varies slightly in the three models.

Table 2. Results of Executing the ACO Algorithm

Nurse	General Practitioner	Specialist Practitioner	radiologist	Min_Los
2,789	4	3,689	3	175
3,9	3,11	4	3,742	161,05
3	2,925	3,653	2,774	196,4
4	2,887	2,684	2,966	203,55
3,323	3,725	3,952	3,623	162,3
3	3	2,856	3,423	184,7

Table 3. Simulation Results for the Three Proposed Models

	Benchmark model	1rst model	2nd model	3rd model
Waiting time for a nursing consultation	90.5	70.4	72.3	60.7
Waiting time for a medical consultation	72.7	50	60.8	63.7
Waiting time for a specialist consultation	94.3	60.6	63	74.4
Waiting time for radiologist consultation	68	50	53.3	60.4
nursing consultation	19	17	18	17
medical consultation	13.3	14.5	12.7	13.7
Specialist consultation	17	17.2	18	16.5

radiologist consultation	14	13.4	14.1	13.4
length of stay (LOS)	350.5	260.7	269.87	254.3
door-to-doctor time (DTDT)	95	80.4	78.7	67

4. Conclusion

Emergency departments face increasing challenges such as overcrowding and limited resources. In many nations, overcrowding in emergency rooms is a serious issue that results in issues for both patients and staff, such as longer wait times, longer stays, and medical blunders. Among the problems facing decision-makers is identifying appropriate human resources with the random influx of patients at different times. This study proposed a new approach based on simulation using Colored Petri net and ACO algorithm. A good study has been conducted of the various operations performed at the emergency department level. A simulation model was designed as a prototype and Benchmark. The ACO algorithm was used to determine Human Resources by calculating LOS. Based on the results obtained through the ACO algorithm, three different simulation models are built, each model depending on its own resources. Simulations were performed for the three models and the results obtained were compared with the Benchmark model. Through this approach, appropriate human resources are obtained with a random flow of patients, thus minimizing both LOS and DTDT. The main problem remains finding a way to calculate LOS and DTDT accurately, so that it facilitates the use of optimization algorithms.

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