Menemui Matematik
(Discovering Mathematics)
journal homepage: https://persama.org.my/dismath/home

Discrete Event Simulation To Reduce Patient Waiting Time Problems In The Emergency Department

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Received: 5 February 2025
Accepted: 23 April 2025

ABSTRACT

Emergency department is one of the busiest department in the hospital. In this project, we use Discrete Event Simulation (DES) to discover patient flow in the emergency department (ED) and at the same time to minimize the patient waiting times. There are three queues that have been considered which are triage, general assessment and additional examination with human resources (nurses and physicians). The positive outcomes observed and it shows significant improvements in average waiting times for various scenarios. Moreover, comparisons between different cases highlight the potential of DES, showcasing noteworthy reductions in waiting times when doubling patient loads. The findings emphasize the transformative impact of integrating DES into emergency department management, offering valuable insights for healthcare systems aiming to optimize resources and improve overall quality of ED.

Keywords: discrete event simulation; emergency department; patient flow; waiting time

INTRODUCTION

An emergency department (ED), also known as an accident and emergency depart- ment (A&E), emergency room (ER), emergency ward (EW), or casualty department, is a med- ical treatment facility that specialises in emergency medicine, where patients can get treatment without making an appointment to see a doctor either by riding in their own vehicle or by am- bulance. Due to the unpredictable number of patients coming to the ED, the department needs to be fully equipped to treat all types of illnesses, some of which may be life-threatening and require immediate attention. ED in most hospitals operate 24 hours a day although there will a lack of staff at some time to accommodate the patients.

ED in hospitals are extremely complex systems with limited resources such as beds, physicians, nurses, laboratories and imaging facilities. The system has gotten more complicated and volatile as a result of the stochastic nature of the majority of these resources (Abo Hamad, 2011). Due to too many people coming to the emergency department non-stop, the waiting room becomes more and more full and this causes patients to have to wait longer which result in ex- cessive patient waiting time. This problem should be taken seriously as emergency departments is one of the important departments in the hospital and the flow of patients in this department should run smoothly so that all patients get the treatment they deserve without having to wait too long.

Due to the lack of resources in the ED, the flow of patients in the department has become increasingly congested because they have to undergo treatment with sufficient equipment.With sufficient equipment, the number of patients who can be treated will increase and achieve patient satisfaction who come to the ED. Increased demand for additional medical services in conjunction with limited resources is straining the capacity of present healthcare delivery in many hospital settings, resulting in high wait times and poor service quality. As a result, there is an urgent need to improve efficiency, which implies improving service quality while using fewer resources, and capacity, which means servicing more patients in a given period (Vissers, 2005) . Thus, this shows that critical resources can influence the patient waiting time in ED.

In this research, we discuss the usage of one such technique, discrete-event simulation (DES), and show how such a model may be built, validated and used to identify waiting time improvements. DES models are computer programmes that simulate the logical flow of complicated processes that occur at discrete periods, using random numbers to imitate their intrinsic variability (for example, arrival and service times). Model validation is carried out by simulating processing times with real data and ensuring that the model outputs reasonably match the actual system outputs. With the advent of more powerful computers and software, DES has become a very powerful instrument that has been employed in many industries, including manufacturing, banking, transportation, and hospitality, as well as natural systems in physics, chemistry, biology and economics.

Overcrowding in emergency departments (EDs) is a serious global issue that has been declared a national emergency in various nations and one of the busiest departments because there are so many patients come to ED at the same time in one day. Lack of staff and limited resources such as doctors, nurses, and beds cause the flow of patients to slow down. However, the ED's congestion is also influenced by the resources and operations of other departments, particularly inpatient pathways (Jones et al., 2009). To overcome this problem, we need to maximize the patient flow in order to minimize the patient waiting time.

Daldoul et al. (2018) proposed the stochastic model and considered six main activities which are triage, general assessment, surgical assessment, auxiliary examinations (X-rays and/or clinical laboratory tests), life-threatening emergencies (SAUV), and bed assignment in the ED of La-Rabta Hospital. One of Monte Carlo methods called Sample Average Approximation (SAA) has been used to solve stochastic programs. The SAA method is used to estimate the mathematical expectations in the objective function. We focus under this research to get some ideas of the situations happen in the ED.

The purpose of this research is to improve the patient flow by minimizing the patient waiting time with the critical resources in the ED of La-Rabta Hospital. In this research, only three queues will be considered which are triage, general assessment and additional examination only. Discrete event simulation (DES) will be used to analyze the patient flow using human resources (physicians and nurses) by changing the allocation of nurses and physicians based on the different cases happen in the ED.

LITERATURE REVIEW

A few years ago, there are number of studies to improve the patient flow in the ED. To increase patient flow, an effective decision-making tool has been developed for the best allocation of service providers in ED while minimizing health care delivery costs and patient satisfaction. First, a queuing-theory based model for a simple ED is described as a basic case study for the genetic algorithm. Then, for a complex ED, a Discrete Event Based simulation model will be presented. Finally, a genetic algorithm-based optimisation methodology with time and cost optimisation objectives is presented and applied to the two models (Memari et al., 2016).

The patient emergency pathway in the ED was enhanced in an integrated framework in this study to maximise patient flow and reduce length of stay for patients in the ED and the entire system. To meet several performance criteria, an objective mathematical model was built while taking into account the ED's limits and limited resources. To solve the suggested ED model under a variety of performance constraints, simulation and optimisation techniques are combined. The proposed model's impact on waiting time performance, patient duration of stay in the ED, and the entire system was examined and addressed. The usage of beds and doctors' resources was optimised and confirmed using real-world data (Allihaibi et al., 2017).

Daldoul et al. (2018) performed a study about a stochastic model to minimize patient waiting time in an emergency department. In this study, the problem that the author focuses is to improve the patient flow in the ED . It is shown that allocation of human and material resources gave impact to the patient flow. The objective of this research is to improve patient flow with consideration of the time constraints and limited resources. Stochastic mix-integer programming (MILP) model has been used to optimize the critical resources in the ED. The goal is to enhance patient flow and satisfaction by lowering the average total patient waiting time from ED arrival to hospitalisation and establishing the appropriate allocation of human and material resources (physicians, nurses, and beds). They used SAA method for solving the stochastic program. In our study, we are going to use another method which is Discrete Event Simulation (DES) to minimize the patient waiting time in the ED .

Through the literature review, there are a few studies that used simulation approach to reduce waiting time. In our study, we are going to use another method which is Discrete Event Simulation (DES) with the same stochastic model to minimize the patient waiting time in the ED of La-Rabta Hospital proposed by Daldoul et al. (2018). The model is to minimize patient waiting time considering the uncertainty of the number of patient arrivals and their service time.

METHODOLOGY

In this chapter, we will continue the research from Daldoul et al. (2018) by proposing discrete event simulation (DES) to analyze the patient flow in the ED of La-Rabta Hospital and reduce the patient waiting time at the same time. Arena Simulation Software will be described and the ED Simulation Model will be presented.

Discrete Event Simulation

A discrete-event simulation (DES) models represents a sequence of event as a discrete time in the operation of a system. Each event occurs at a specific point in time and represents a change in the system's state. The simulation time can directly jump to the occurrence time of the next event, which is known as next-event time progression because no change in the system is believed to occur between consecutive events.

Zeinali et al. (2015) proposed discrete event simulation (DES) model combined with suitable metamodels. This is used as a novel decision support system to improve the patients flow and relieve congestion by changing the number of ED resources (the number of reception- ists, nurses, residents, and beds). Then the proposed model is used to minimize the total average waiting times of patients subject to both budget and capacity constraints.

DES has been used by Nun˜ez-Perez et al. (2017) to analyse patient flow at ED in a district general clinic. However, its application has not been extended to evaluating the impact of improvement initiatives. So, the authors proposed to use DES and test operational methods for improved ED. Following that, the DES model is created and verified to determine whether it is statistically equivalent to the real world. The performance metrics of the present system are then computed and analysed. Finally, ideas for improvement are offered and evaluated using computer models and statistical tests.

A simulation model was used to analyze the resource capacity required in the ED department to help reduce patient waiting times. the author has used the data that has been collected for 24 hours to develop a simulation model. Arena simulation was used to replicate the real ED procedures of a public hospital in Selangor, Malaysia. OptQuest optimization also is used to identify the best combinations of a variety of resources to reduce patient wait time while increasing the number of patients serviced (Ibrahim et al., 2017).

Arena Simulation Software

Arena is a discrete event simulation and automation software developed by Systems Modeling in 1993, which was later acquired by Rockwell Automation. Arena has been the top choice for discrete event simulation software for the past 30 years. The program's success can be explained by its extensive functional, object-oriented interface and ability to adapt to many application areas. To design a model, start by creating a sequence of blocks from a pre-defined library of objects. Then, establish numerical attributes and describe probable patterns to generate random occurrences and numbers (Guseva et al., 2018).

In this study, Arena Simulation Software will be used to create a simulation model of the ED of La-Rabta Hospital and then analyze the queuing at the ED using the simulation result. Arena programme increased visibility into the impact of a system or process modification by providing toolbar and menu access to common simulation actions like animating the model, running the model, and viewing the results.

Algorithm

Algorithm 1 Discrete Event Simulation using Arena Software

Require: Arena Simulation Software
1: Open or create a new simulation model
2: Define the simulation entities (e.g., patient, nurse, physician)
3: Define the processes or activities (triage box, general assessment, additional examination)
4: Define the resources (nurses, physicians)
5: Define the service times distribution for each activity (2 Hours)
6: Run the simulation

Algorithm 1 shows the algorithm for discrete event simulation. First, a new model is produced using Arena Software. The first step is to create a new model using Arena Software. Next, the entities used in this study are defined: patients, nurses, and physicians. Then the simulation's processes are established, such as the triage box, general assessment, and additional examination. The resources used are then defined, including nurses and physicians. After defining the service time distribution for each step, specifying the time unit as 2 hours, and lastly running the simulation.

ED Simulation Model

ED simulation model has been created using Arena software and patients are divided into two types which are Type 1 and Type 2. Both types of patients have different type of characteristics. For patient Type 1, they are more serious injury than patient Type 2. First of all, patients that come to the ED will through to the first process which is triage box. In this process, the patient will queue for triage nurse to collect patient's health information such as blood pressure, body temperature and heart rate. Next, physicians will handle the general assessment queue and decide whether the patient need to do additional examination or not. For Patient Type 2, they can straightly back home without to do the additional examination but Patient Type 1 will go to the additional examination queue to check for their serious injury. After that, the patient will be assign as Patient Type 2 and go back to general assessment queue again. Then, the patient finally back home after done the assessment.

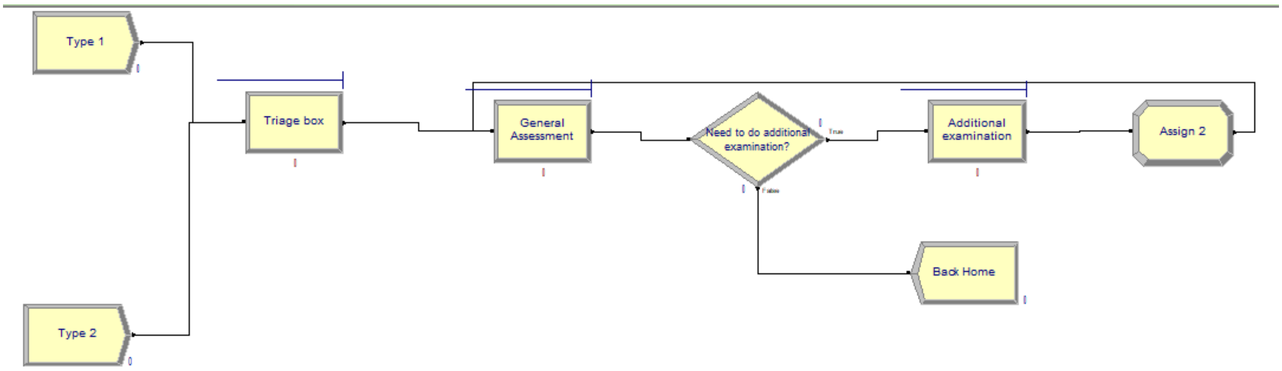

Figure 1: ED Simulation Model

PATIENT WAITING TIME PROBLEMS IN THE EMERGENCY DEPARTMENT

Patient Waiting Time Problem

Based on critical resources in the ED at the La-Rabta Hospital in Tunisia by Daldoul et al. (2018), stochastic model has been proposed to overcome this problem. The goal is to analyse the interactions between these various resources and identify the optimal allocation in order to reduce total waiting time while taking into account the various constraints.

In this mathematical model, three queues has been considered. The first queue is for the triage patients (q=1), two assessment queues such as general assessment (q=2) and the third queue is for additional examinations assured by nurses (q=3).

First of all, patient arrivals to the ED denote as A_t and they need to wait ($W_{t,1}$) before go to triage box. The patient that are from triage box ($S_{t,1}$) will wait ($W_{t,2}$) to be transferred to the general assessment based on acuity level with coefficients α .

For the patient served in the box of general assessment ($S_{t,2}$), there are two situations that should be considered either needs additional examination ($\beta S_{t,2}$) or sent back home. After that, patients that need to go to the additional examination have to wait ($W_{t,3}$) before being serve. Next, for the patients that has been served in the additional examination box ($S_{t,3}$), they will come back for a second general assessment ($\lambda S_{t,3}$).

Parameters

Parameters	
T	Planning horizon
t	Different period of the day [1,T]
I	The number of different types of human resources
i	A type of human resources available [1,I]
Q	The total number of queues
q	A queue number [1,Q]
Ni,q	The total number of each human resource i , $\forall i \in [1,I], \forall q \in [1,Q]$
n	Number of resources of each type $[1,N_{i,q}]$
α	Coefficient associated with the patient flow served in the triage
β	Coefficient associated with the patient flow served in the box of general assessment , $\forall j \in [1,3]$
λ	Coefficient associated with the patient flow served in the box auxiliary examination
$A_t(\omega)$	Random variable representing the number of patient arrival in period t, under scenario ω
Li,n,t,q	Random variable representing the service time, which is the number of patients that n resources of type i can serve during period t for each q , under scenario ω

Decision variables

$$x_{i,n,t,q} = \begin{cases} 1 & if\ there\ exactly\ n\ resources\ of\ type\ i\ working\ at\ period\ t, \forall q \in [1,Q] \\ 0 & otherwise \end{cases}$$

Notation	
Pi,t,q	The number of resources of type i at period t $\forall q \in [1,Q]$
$W_{t,q}(\omega)$	The number of patients that are waiting in queue q at the start of period t, under scenario ω
$S_{t,q}(\omega)$	The number of patients in queue q that have been served during period t, under scenario ω

Stochastic Mathematical Model

The objective function in this model is to minimize patient waiting time in ED

$$minE_w \left[\sum_{t=1}^{T} \sum_{q=1}^{Q} (W_{t,q}(\omega) - S_{t,q}(\omega)) \right] \tag{1}$$

The objective function (1) is to estimate total patient waiting time accumulated based on all scenarios.

$$W_{1,1}(\omega) = A_1(\omega) \tag{2}$$

$$W_{1,q}(\omega) = 0 \ \forall q \in [2,Q] \tag{3}$$

$$S_{1,q}(\omega) = 0 \ \forall q \in [1,Q] \tag{4}$$

Number of patients that are in the queues in each scenario can be initialize as stated in constraint (2) until (4).

$$W_{t,1}(\omega) = W_{t-1,1}(\omega) + A_1(\omega) - S_{t-1,1}(\omega) \ \forall t \in [2,T] \tag{5}$$

$$W_{t,2}(\omega) = W_{t-1,2}(\omega) + \alpha S_{t-1,1}(\omega) + \lambda S_{t-1,3}(\omega) - S_{t-1,2}(\omega) \ \forall t \in [2,T] \tag{6}$$

$$W_{t,3}(\omega) = W_{t-1,3}(\omega) + \beta S_{t-1,2}(\omega) - S_{t-1,3}(\omega) \ \forall t \in [2,T] \tag{7}$$

Number of patients in each queue at every period will be update from constraint (5) until (7).

$$S_{t,q}(\omega) \leq W_{t,q}(\omega) \ \forall t \in [1,T] \ \forall q \in [1,Q] \tag{8}$$

Constraint (8) defines a logical limit for the number of patients served during a certain period. This number cannot be greater than the number of patients waiting in queue.

$$S_{t,1}(\omega) \leq \sum_{n=1}^{N_{2,1}} L_{2,n,t,1}(\omega) * x_{2,n,t,1} \quad \forall t \in [1, T] \tag{9}$$

$$S_{t,2}(\omega) \leq \sum_{n=1}^{N_{1,2}} L_{1,n,t,2}(\omega) * x_{1,n,t,2} \quad \forall t \in [1, T] \tag{10}$$

$$S_{t,3}(\omega) \leq \sum_{n=1}^{N_{2,3}} L_{2,n,t,3}(\omega) * x_{2,n,t,3} \quad \forall t \in [1, T] \tag{11}$$

In constraint (9) until constraint (11), the number of patients that has been served in each queue at every period will be limited.

Data

In this research, we used the real data of patient's arrival at ED of La-Rabta Hospital by Dal- doul et al. (2018) as shown in Figure 2. Table 1 shows the number of patients arrival collected from 8:00 am until 4:00 pm for every 2 hours. It is clear that more patients arrive to the ED between 8:00 a.m. and 4:00 p.m., which is a critical time period. As a result, the allocation of nurse and physician is important to ensure that the patient flow in the ED runs properly.

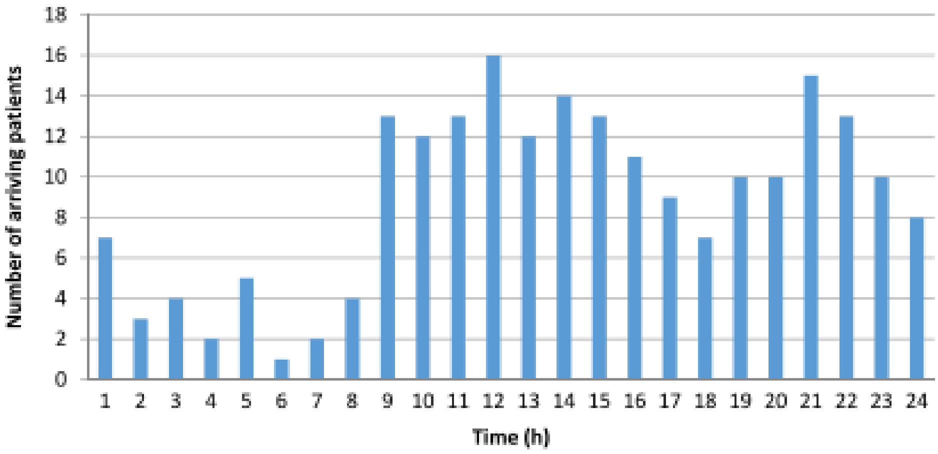

Figure 2: Number of patient arrivals per period

Table 1: Number of patient arrivals

Period	Number of patients
8:00 - 10:00	23
10:00 - 12:00	29
12:00 - 14:00	26
14:00 - 16:00	24

Table 2 shows that the number of patient arrival have different probability for patient type 1 and patient type 2. For scenario A, the probability is 50% for type 1 and 50% for type 2. Next, the probability is 30% and 70% for type 1 and type 2 respectively. It can be shown that there will more patient will back home for type 2. Lastly, probability patient type 1 and type 2 are 60% and 40% for scenario C. So, there will be more patient type 1 will go to Additional Examination process.

Table 2: Probability of patient arrival for patient Type 1 and Type 2

Scenario	Patient Type 1	Patient Type 2
A	50%	50%
B	30%	70%
C	60%	40%

Table 3 shows the service times distribution that are used to create the ED simulation model for every stage. We set up Poisson (3.13) for patient arrival, Normal (4.2) for triage, Exponential (9) for general assessment, and Exponential (15) for additional examination.

Table 3: Service times distribution

Stage	Distribution
Patients' arrival	Poisson (3.13)
Triage	Normal (4,2)
General Assessment	Exponential (9)

Example

In this section, Case 1 and Case 2 are run using Arena with different allocation of nurses and physicians. After that, the simulation results for both situations will be compared.

Table 4 shows different allocation of nurses and physicians for Case 1 and Case 2. The allocation for Case 1 is based on Daldoul et al. (2018) paper, which are the number of nurses on triage and additional examination is 1 nurse and 2 physicians on general assessment. In this research, we analyzed the patient flow for Case 2 by increasing the number of physicians from 2 physicians to 4 physicians and remaining the number of nurses on triage and additional examination.

Table 4: Different Allocation of Nurse and Physician

Number of Patients	Case	Number of Nurse at Triage	Number of Physician	Number of Nurse at Additional Examination
102	1	1	2	1
102	2	1	4	1

Comparison between Case 1 and Case 2

Table 5: Comparison between Case 1 and Case 2

	A	B	C
Patient	102	102	102
Type	1 : 50% 2 : 50%	1 : 30% 2 : 70%	1 : 60% 2 : 40%
Go home (Case 1)	56	60	44

Average Waiting Time (Case 1) (min)	230.31	224.84	191.85
Go home (Case 2)	79	93	61
Average Waiting Time (Case 2) (min)	142.58	118.78	150.17

Between Cases 1 and 2, it can be seen that Case 2 has a lower average waiting time than Case 1. Before adding a physician to the general assessment, the average waiting time for Case 1 in scenarios A, B, and C is 230.31 minutes, 224.84 minutes, and 191.85 minutes, respectively. After adding extra physicians, the average wait time for Case 2 is 142.58 minutes for scenario A, 118.78 minutes for scenario B, and 150.17 minutes for scenario C. It may be argued that the allocation of nurses and physicians for Case 2 is superior to Case 1, as indicated in Table 5.

RESULT

Experimental Design

We obtained a set of data with 102 observations for number of patient arrivals at the ED from Daldoul et al. (2018) between 8:00 a.m to 4:00 p.m . In order to analyze the patient flow in the ED, we generate more data by doubling the number of patient arrivals from the real data.

After we generate the data, we obtained a set of data with 204 observations for patient arrivals at the ED. The allocation of nurse and physician will be different for each case to overcome the patient waiting time problem when the patients are doubled.

The problems are divided into two parts which are Problem 1 and Problem 2. For Problem 1, we run the simulation for scenario A, B and C for every 2 hours but for Problem 2, we run the simulation only for scenario B for 8 hours with different allocation of nurse and physician.

Generate Data

Data has been generated from the real data by Daldoul et al. (2018) and Table 6 shows the number of patient arrivals when doubled.

Table 6: Number of patient arrivals when doubled

Period	Number of patients
8:00 - 10:00	46
10:00 - 12:00	58
12:00 - 14:00	52
14:00 - 16:00	48

Problem 1

In this section, four more cases which are Case 3, Case 4, Case 5 and Case 6 will be run one at a time with different allocation of nurse and physician using Arena. The simulation results for Case 3 will be compared with Case 4 while the simulation results for Case 5 will be compared with Case 6.

Table 7: Different Allocation of Nurse and Physician

Number of Patients	Case	Number of Nurse at Triage	Number of Physician	Number of Nurse at Additional Examination
204	3	1	2	1
204	4	1	4	1
204	5	2	4	2
204	6	2	7	2

Table 7 shows the different allocation of nurse and physician for Case 3 until Case 6. For Case 3, the number of nurses and physicians are follow to Case 1 while Case 4, the number of nurses and physicians are follow to Case 2. From that, the number of patients that are in the queue can be analyze if the number of patients are doubled. Next, for Case 5, number of nurse at triage and additional examination become 2 nurses at each process. Lastly, for Case 6, number of physicians are added 3 more physicians from Case 5 become 7 physicians and the number of nurses remain same.

Comparison between Case 3 and Case 4

Table 8: Comparison between Case 3 and Case 4

	A	B	C
Patient	204	204	204
Type	1 : 50% 2 : 50%	1 : 30% 2 : 70%	1 : 60% 2 : 40%
Go home (Case 3)	62	47	56
Average Waiting Time (Case 3) (min)	291.25	302.08	305.83
Go home (Case 4)	86	95	80
Average Waiting Time (Case 4) (min)	251.13	231.71	239.51

After doubling the number of patients in Case 3 and utilising the same allocation of nurses and physicians as in Case 1, the average waiting time for scenarios A, B, and C is 291.25 minutes, 302.08 minutes, and 305.83 minutes, respectively. Case 4 had shorter average waiting times than

Case 3, with 251.13 minutes for scenario A, 231.71 minutes for scenario B, and 239.51 minutes for scenario C. It is clear that as the number of physicians increases, so does the number of patients that are going home.

Comparison between Case 5 and Case 6

Table 9: Comparison between Case 5 and Case 6

	A	B	C
Patient	204	204	204
Type	1 : 50% 2 : 50%	1 : 30% 2 : 70%	1 : 60% 2 : 40%
Go home (Case 5)	73	87	70
Average Waiting Time (Case 5) (min)	142.17	129.87	139.17
Go home (Case 6)	135	184	136
Average Waiting Time (Case 6) (min)	119.00	55.56	92.21

Table 9 shows that Case 6 has a lower average waiting time than Case 5. When there are two nurses for triage and additional examination, the average wait time for Case 5 is 142.17 minutes for scenario A, 129.87 minutes for scenario B, and 139.17 minutes for scenario C. After adding the number of physicians from the allocation nurses and physicians of Case 5, the average waiting time for scenarios A, B, and C becomes 119.00 minutes, 55.56 minutes, and 92.21 minutes respectively.

Problem 2

The simulation results for Scenario B carried out simultaneously with different allocations of nurses and doctors will be compared.

Table 10: Scenario B , 8 Hours

Allocation Number of Staff	**1**	**2**	**3**
Nurse at Triage	2	2	4
Physician	4	7	7
Nurse at Additional Examination	2	2	4
Patients	204	204	204
Total Waiting Time	152.75	128.18	22.46
Number of patients at Triage	0	0	0
Number of patients at General Assessment	74	2	1
Number of patients at Additional Examination	0	0	0
Back Home	120	202	203

Table 10 shows the results of the test problem for scenario B with doubled patients, which is performed for 8 hours with varying allocations for nurses and physicians. For allocation 1, the total patient waiting time is 152.75 minutes. Next, the total patient waiting time for allocation 2 is 128.18 minutes. Finally, allocation 3 achieved the best results, with four nurses at triage, seven physicians at general assessment, and four nurses at additional examination. The total patient waiting time is 22.46 minutes.

CONCLUSION

In this research, it shows that Discrete Event Simulation (DES) can be an effective approach for addressing patient flow issues in the emergency department. The implementation of DES not only improved operational efficiency but also significantly reduced patient waiting times. Despite these challenges, the positive results indicate that DES has considerable potential for improving emergency department operations and patient experiences.

Case 2 shows that the average waiting time in Case 1 for scenarios A, B, and C has been lowered to 38.03%, 47.17%, and 21.70%, respectively. The comparison table between Case 3 and Case 4 shows that doubling the patient reduces the average waiting time to 13.79%, 23.29%, and 21.67%, respectively. The comparison table between Case 5 and Case 6 shows that the average waiting time has been reduced to 16.28%, 57.20%, and 33.79% for scenarios A, B, and C.

As healthcare systems improve, further study in this field is needed to investigate various aspects of patient flow and waiting time reduction, resulting in more comprehensive and successful use of DES in emergency healthcare settings. Additionally, comparative studies with other optimization methodologies may offer a more nuanced understanding of the most effective strategies for emergency department management.

In conclusion, this research underscores the transformative impact of integrating DES into emergency department management. As healthcare systems continue to evolve, the lessons learned from this study emphasize the importance of adopting innovative methodologies to address the challenges inherent in emergency care. By doing so, we move closer to a future where patient waiting times are minimized, resources are optimized, and the overall quality of emergency healthcare is significantly improved.

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