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SIMULATION-BASED OPTIMISATION FOR REDUCING WAITING TIMES IN THE EMERGENCY DEPARTMENT

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Abstract
The increasing number of admissions to emergency department (ED) has become a significant issue in both Turkey and globally. The reasons for the high preference for emergency departments include the fact that they are free of charge, they provide 24-hour service, they have easier access to doctors compared to outpatient clinics, and non-emergency patients can also apply. Additionally, the complex interactions between fluctuating workloads, unpredictable arrival rates, and limited resources make it difficult to optimise the flow in EDs. This complexity leads to overcrowded emergency services, long length of stay (*LOS*), and burnout among healthcare professionals. In this study, a simulation model was developed to optimise the unbalanced demand of the ED with unpredictable patient flows and resource constraints. Different scenarios were designed using Arena simulation software, and optimisation was performed on the Arena/OptQuest platform. As a result, performance improvement was achieved by reducing patient wait times and enhancing service delivery.
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Key Words: Emergency Department, Discrete Event Simulation (DES), Optimisation, Length of Stay, Constraint Theory

1. INTRODUCTION

In the globalised world, with the increasing population, healthcare services are under pressure to provide higher quality service in less time and at lower costs. However, existing management models may not be able to respond chronic healthcare service issues. Traditional solutions to address this problem are often those that increase the number of resources or require investment. However, the focus should be on improving efficiency by utilising existing resources. Despite increasing resources allocated to health care, lack of capacity and time are still chronic problems worldwide [1].

The ED is a unit with high patient arrival rates and intensive working tempo among hospital units. Frequent use of EDs by the elderly population, limited access to other resources and excessive use of EDs for the treatment of non-emergency health problems are among the main factors leading to an increase in the number of patients admitted to this department [2]. EDs are among the most important departments of hospitals in terms of providing the fastest intervention to patients. Due to the uncertainty of parameters such as patient arrivals and waiting times, the behaviour of EDs is quite complex [3]. Improving the flow of EDs is a priority worldwide [4]. The ED functions as an intermediary station rather than a destination that accepts all patients without distinguishing between types of patients or specialties. This situation can lead to overcrowding in EDs. Overcrowding in the ED increases the likelihood of harming patients and reduces patient satisfaction. It can prolong the patient's physical and emotional pain, worsen their clinical conditions, lead to preventable complications, and increase mortality rates. Studies have reported the negative outcomes of this situation for both patients and staff [5, 6]. Crowded EDs also reduce job satisfaction and productivity, leading to burnout among staff. During periods of overcrowding, staff experience increased stress levels, including exposure to violence and a decrease in adherence to clinical guidelines [7]. Although ED overcrowding is considered a national crisis, it is actually an international phenomenon.

Therefore, ED and hospital processes need to be redesigned to streamline patient flow [8]. The study addresses the constraints of the ED, which has a stochastic and dynamic structure. The aim of this study is to establish an ED simulation model and, by removing the constraints, improve the performance of the ED using Arena/OptQuest in a way that minimises the patient's length of stay in the system.

In EDs, key factors such as bed availability, the number of doctors, and laboratory capacity directly impact patient waiting times. Therefore, it is crucial to meet the demand for ED resources. Given the stochastic nature of emergency service demand, resource allocation is complex and dynamic. Decision-makers often use quantitative analysis, with simulation modelling being an effective method for solving dynamic resource allocation problems with constraints [9]. Simulation is a method that helps to more clearly define the effects of changes to the system by modelling real-world situations [10]. It has become increasingly widespread due to its ability to ensure controlled changes in existing systems without intervening in real systems, while also allowing for the prediction of the impact of potential different conditions on performance in new systems. DES provides decision-makers with the opportunity to create complex models, rapidly test "what-if" scenarios on ongoing activities, and explore different tactics to adopt new strategies [11, 12]. Therefore, in this study, DES has been used. The Arena/OptQuest platform has been used for testing "what-if" scenarios. By using Arena/OptQuest, patient waiting times are optimised, and the ideal resource allocation is achieved.

This research is organised as follows. Section 1 explains the problem and covers the purpose of the study. Section 2 provides a comprehensive review of the relevant literature. Section 3 includes the system definition, introduction of the dataset, statistical distribution phase of the data, analysis of the current state processes of the emergency service system, workflow, and optimisation of the simulation model. Section 4 presents the real system performance, the examination of the newly designed simulation-based optimisation approach, and the details of the optimisation obtained with OptQuest. Finally, Section 5 presents and discusses the results of the study and suggests potential methods for future research.

2. LITERATURE REVIEW

Identifying the appropriate modelling approaches to gain a better understanding of a system and accurately measure its performance and efficiency is crucial for its future development.

The outputs of quantitative models are typically expressed in terms of system performance and efficiency. The performance of a system can be measured using DES [13]. DES is a decision support technique used to understand the behaviour of a system by simulating its operations and to apply various strategies [14]. DES is an effective technique used to examine and enhance dynamic systems that involve stochastic demands, service times, and complex process interactions. The DES model is regarded as the most effective method for improving system outputs when the optimiser faces uncertainty in system parameters, such as the arrival rate of ED (ED) patients or the length of the patient queue [15]. There are numerous studies in the literature that use the DES model. It has been found that the most popular DES software is Arena and Simul8.

When some studies from the literature are compared with this article; Aboueljinane et al. [16] adopted a DES-based optimisation approach in emergency medical services and achieved performance improvements using OptQuest. However, the distribution of incoming patients was planned according to 4 time zones on weekdays and 2 time zones on weekends. In the study under consideration, patient arrivals were distributed across 24 hourly time slots, allowing for a more precise determination of arrival patterns. Huang et al. [17] analysed bottlenecks in the ED treatment process and proposed an optimised management strategy. Patient arrivals were analysed using three months of data. In this study, considering one year of patient data makes the patient distributions more representative of real conditions. Yousefi et al. [18] conducted a literature review of 38 studies published between 2007 and 2019 that applied optimisation-based simulation methods in hospital EDs. An analysis of the software used for simulation in these studies reveals that Rockwell Automation Arena is the most commonly utilised, accounting for 37 % of the 38 studies. This statistic supports the selection of Arena in this study. Zeinali et al. [19] developed a decision support system using DES and metamodels to reduce patient overcrowding and long waiting times in hospital EDs. By optimising resource configurations, the model reduced waiting times by 48 %. The accuracy and efficiency of the proposed model were validated through comparisons with OptQuest, yielding successful results. Ibrahim et al. [20] employed OptQuest optimisation to identify resource combinations that minimise patient waiting times while increasing the number of patients served. This study highlights the potential of integrating DES with OptQuest to enhance resource management in EDs.

The existing literature reveals a lack of comprehensive studies that integrate performance evaluation and optimisation from the perspective of DES in healthcare systems. [21]. In order to fill this critical gap, the integration of DES and optimisation is preferred in this study. DES will focus on increasing system efficiency by reducing the bottleneck within the system. The aim of this study is to find the optimal parameter combinations that will maximise system performance using the OptQuest platform, which integrates with Arena and is effective in solving complex problems with numerous variables and constraints. OptQuest is a modern software used for solving complex problems [16].

The use of one year of real patient data from the largest hospital's ED in the region makes this study stand out compared to others. When the models are examined in the literature, simulations based on 1 day, 1 month, etc. data were found. However, patients come to the ED in different numbers and intensities according to seasonal and environmental conditions. Therefore, models using small datasets may not accurately represent reality and lack the necessary dynamism to truly improve system performance. Additionally, patients arriving over the course of one year were divided into 24 hourly time slots, and different Create modules were set up in the Arena program based on 24 distinct distributions. This approach will improve the accuracy of patient arrival intensity in the system and increase the precision of queues that form within the system. In the reviewed studies, one day is often divided into several time slots or weekly distributions are planned. This, in turn, is another strong and unique aspect of this study. Additionally, in the models established in the literature, incoming patients are generally not divided into different groups, or they are categorised into only a few distinct groups. However, when analysing incoming patients, it has been determined that there are subgroups within the system, such as patients staying for 0–10 minutes, those coming for prescriptions, outpatient-treated patients, patients who underwent tests (blood work, imaging, or both), patients who stayed for long periods or not at all, and patients referred to other departments. The length of time spent in the system and the workflow routes differ between hospitalised and non-hospitalised patients based on their duration of stay in the system. The study categorises patients into 16 distinct subgroups based on these factors and assigns a corresponding workflow route to each patient in detail. This approach enhances the realism of the simulation, and higher performance improvements in system efficiency are anticipated. These specific details make the study distinct and original compared to the literature. Additionally, after the system was run, comprehensive statistical evaluations were conducted using Statistica, and an optimisation model with numerous constraints was developed and a thorough optimisation was carried out using OptQuest. This further contributed to the originality of the study.

3. RESEARCH METHODOLOGY

This section outlines the methodology. In the study, a deterministic model was initially developed to establish the simulation model. This model includes patient admission data, patient flow processes, process times, and resources. Secondly, uncertainties related to activity durations, patient arrival times, and patient care requirements were modelled. Since the simulation software prevents resources from being used by multiple patients simultaneously, resource uncertainty is inherent in the nature of the model. Subsequently, with the integration of these uncertainties into the model, the workflow was simulated in a stochastic environment. Finally, the effects of uncertainties on patient waiting times and time spent in the system were optimised in different scenarios using OptQuest. The steps applied are presented sequentially in Fig. 1.

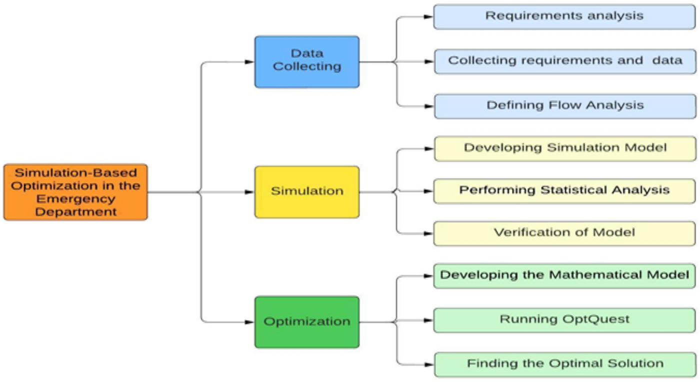

Figure 1: Methodology.

3.1 System analysis

EDs experience varying numbers of patient arrivals at different times of the day. In the analysed system, in order to make the patient arrival distributions more realistic, the day was divided into 24 hourly time slots based on patient arrival frequency. The averages of patient arrivals over the course of one year were calculated, and statistical distributions for hourly patient arrivals were obtained using the Easy Fit program. To determine the ED process times, historical data from the relevant department and expert opinions were utilised. The process flow was prepared based on observations in the ED and discussions with the unit's responsible doctor. The ED operates in two shifts: Shift 1 from 08:00 to 17:00 and Shift 2 from 17:00 to 08:00.

3.2 Simulation model

Among the ED patients categorised into 16 different groups, Group 1 patients stay in the system for less than 10 minutes. All other groups first visit the patient registration section. After the registration is completed, if the patient is only there to get a prescription, they proceed directly to the doctor to have the prescription written. All other patients who come for examination are first taken to Bed 1. In Bed 1, after the patient's history is taken by the assistant doctors, a physical examination is conducted. After this process, Bed 1 is made available for use again. The patient in need of testing is then directed to the appropriate test. During the testing phase, patients visit the laboratory, the imaging department, or both. The post-test evaluation is conducted by the assistant doctor. After the testing phase, if the patient is an inpatient, they are directed to the ward. If not, and the patient is expected to stay for a short period, they are directed to Bed 2. In Bed 2, after the patient's stay is completed, they are directed to the prescription department. Patients who do not require testing are sent directly to the prescription department. The patient, after receiving their prescription, exits the ED. The system's workflow diagram is shown in Fig. 2.

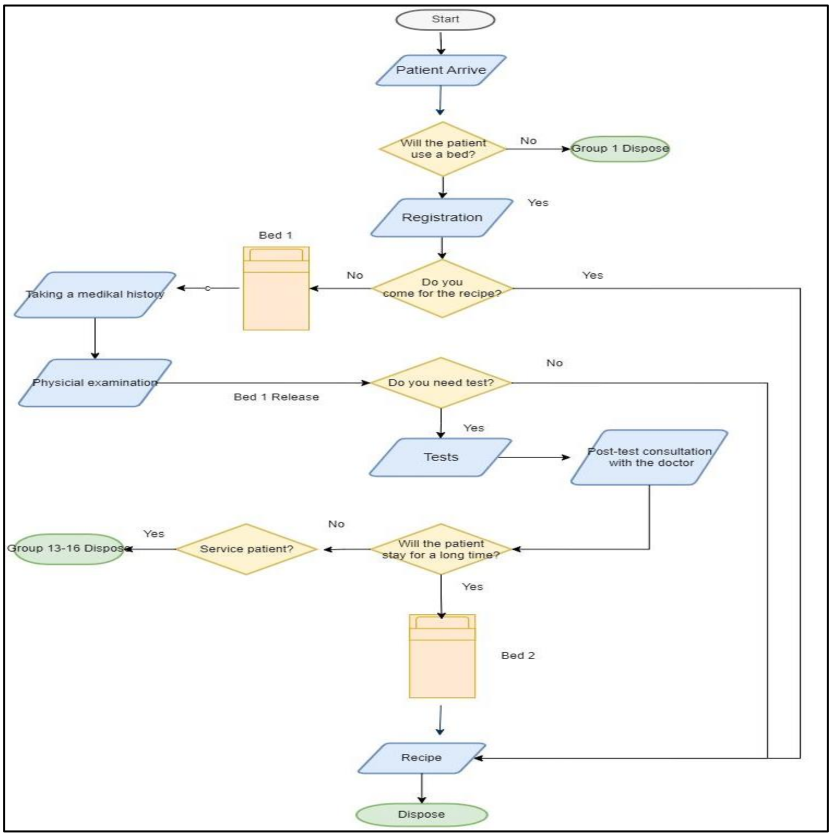

Figure 2: ED workflow diagram.

In the ED analysed in the study, an average of 101 patients are served per day. The ED consists of the following sections: patient registration, triage, X-ray room, laboratory, bed group 1, and bed group 2. The human and material resources initially used are provided in Table I.

Table I: Current situation human and material resources.

Intern Doctor	Assistant Doctor	Image Personnel	Laboratory Personnel	Nurse	Registration Secretary	Bed 1	Bed 2
1	2	1	1	1	1	6	18

3.3 Model validation

In simulation modelling, the alignment of the model with the real system was verified by comparing the average waiting time of a patient in the real system with that of a patient in the model, as well as the number of incoming patients. A triage system is implemented in the ED to ensure effective service. In Turkey, the triage system consists of four categories. Details of these categories are presented in Fig. 3.

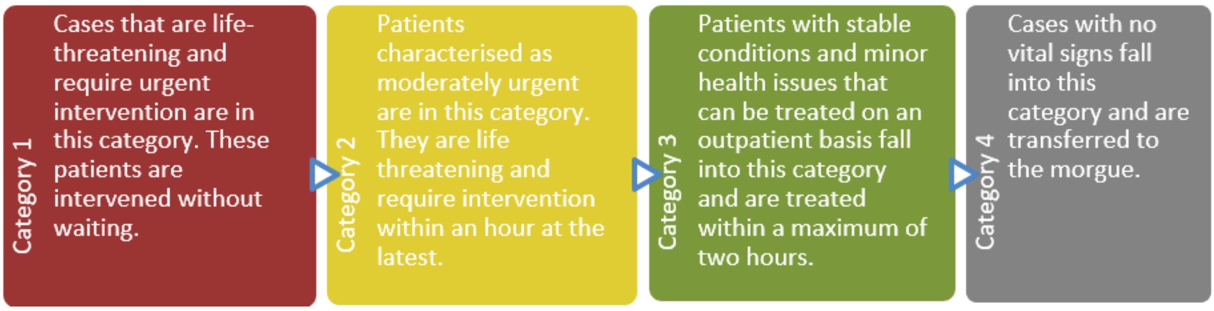

Figure 3: Turkey's triage categories.

The system in the study was designed for living patients, divided into three priority groups: Category 1 (Groups 8-16), Category 2 (Groups 3-7), and Category 3 (Groups 1-2). In the real system, 37452 patients were served in one year, while 37275 were served in the simulation, a 0.47 % difference. This shows the number of patients entering the system is close to reality. The patient distribution by triage category is shown in Table II.

Table II: Comparison of the real and simulated environments according to triage categories.

Group (Number of patients)	Real average	Simulation average	Difference
Category 1 (Red)	4284	4183	2,35 %
Category 2 (Yellow)	25857	25661	0,76 %
Category 3 (Green)	7311	7431	1,64 %
Total	37452	37275	0,47 %

The patients' lengths of stay in the system were compared using the Mann-Whitney U test and the Kolmogorov-Smirnov test in the Statistica software. When comparing the lengths of stay for real data and Arena Simulation data, the difference was found to be less than 3 % for eight patient groups, and between 3 % and 5 % for four patient groups, which is within an acceptable range. The remaining four patient groups were not considered for evaluation as they were service patients. The comparisons of the patients' lengths of stay in the system and their standard deviations are presented in Table III.

Table III: Statistica results.

Group	Real average	Simulation average	Average difference	Real std. dev.	Simul. std. dev.	*p*-value
1	10,4	10,9	4,8 %	2,53	2,59	0,58
2	20,1	20,8	3,48 %	5,62	4,99	0,15
3	44,2	45,3	2,48 %	8,35	12,60	0,15
4	123,0	122,7	0,24 %	46,89	45,51	0,66
5	332,0	347,6	4,6 %	68,73	71,06	0,08
6	682,6	684,7	0,3 %	135,39	173,92	0,59
7	1201,6	1239,8	3,17 %	133,21	142,02	0,07
8	148,1	146,3	1,21 %	56,79	158,45	0,17
9	332,0	329,0	0,9 %	67,32	379,51	0,56
10	698,7	690,7	1,14 %	142,65	244,52	0,05
11	1211,0	1234,0	1,89 %	137,97	279,14	0,93
12	3770,2	3730,6	1,05 %	1653,59	1615,54	0,12

When the results were examined, the *p*-values for the lengths of stay in the system for twelve patient groups were found to be statistically appropriate. In the nonparametric Mann-Whitney U test, a *p*-value greater than 0,1 indicates that there is no statistically significant difference between the distributions of the two sample groups. As an example, histograms of the lengths of stay for Group 7 and Group 11 in both the current system and the simulation system are presented in Figs. 4 and 5. The histograms demonstrate that the lengths of stay in the system are consistent.

Fig. 6 presents the box plot for the lengths of stay in the system for Group 4, while Fig. 7 shows the box plot for Group 12. These graphs illustrate that the lower values, upper values, and averages are consistent.

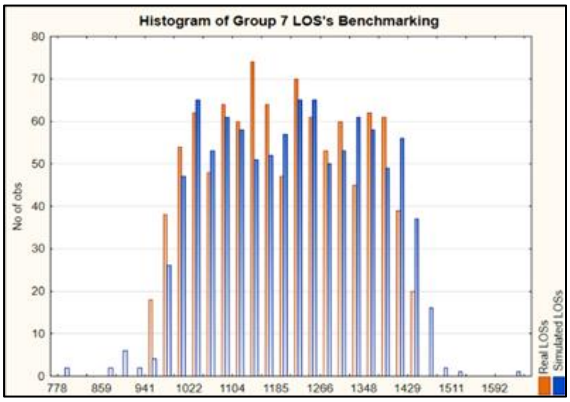

Figure 4: Histogram of group 7 *LOS*.

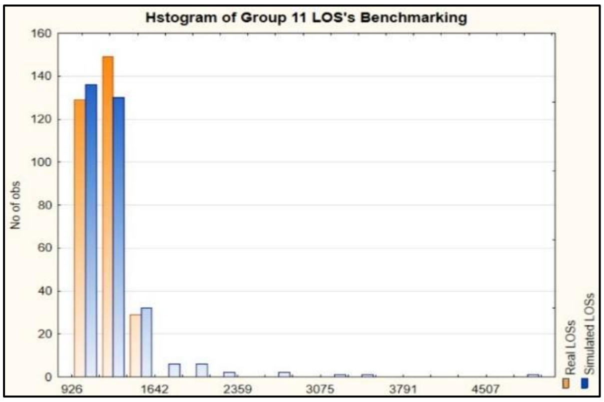

Figure 5: Histogram of group 11 *LOS*.

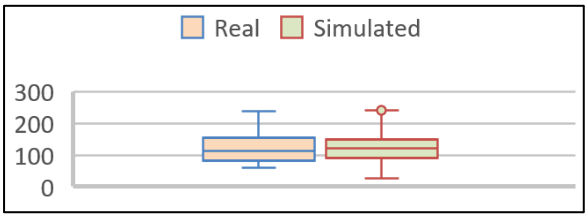

Figure 6: Group 4 *LOS*'s box-plot.

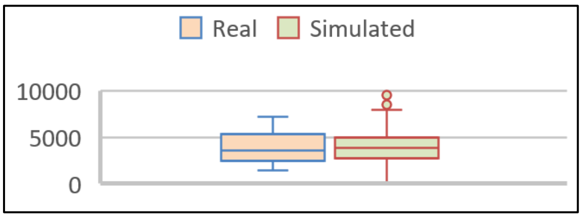

Figure 7: Group 12 *LOS*'s box-plot.

4. FINDINGS AND DISCUSSION

According to the results of the simulation model, the bottlenecks in the system were identified as patients waiting for the Bed 1 group for learning patient history and physical examination, waiting to see the doctor after the tests were performed, and patients who will be hospitalised for a long time waiting for the Bed 2 group. Therefore, reducing the waiting times for Bed 1 and Bed 2 groups will help eliminate the system bottlenecks. To reduce these bottlenecks and decrease patient waiting times in the ED, an optimisation model was developed using the OptQuest function in Arena simulation software. The lower and upper limits for resource constraints were determined based on the available amount of resources that the ED management can provide. In the mathematical model, x_k represents k^{th} resource constraint, where $K = 6$. x_{lk} denotes the lower limit of the k^{th} resource and x_{uk} represents the upper limit of the k^{th} resource. c_k is the cost coefficient associated with the k^{th} resource. t_m represents the waiting time in the queue for the m^{th} bed. t_{um} represents the maximum waiting time for the m^{th} resource. $t_{u1} = 5$ and $t_{u2} = 30$. b_n denotes the number of beds in the n^{th} bed group, b_{ln} represents the minimum number of beds in the n^{th} bed group, b_{un} represents the maximum number of beds in the n^{th} bed group. The objective function and constraints of the model are presented in Table IV.

Table IV: Objective function and constraints.

Objective function	
$Min\ Z = \sum_{k=1}^{K} c_k x_k$	
Constraints	
$x_{lk} \le x_k \le x_{uk}$	for $\forall k$
$t_m \le t_{um}$	for $m = 1, 2$
$b_{ln} \le b_n \le b_{un}$	for $n = 1, 2$
$x_{lk}, x_k, x_{uk}, c_k, t_m, t_{um}, b_{ln}, b_n, b_{un}$	$\in Z$

The lower and upper bounds and cost coefficients for decision variables and resource constraints are given in Table V.

Table V: The lower and upper bounds and cost coefficients for decision variables.

k	x_k	x_{lk}	x_{uk}	c_k
1	Intern Doctors	1	5	1
2	Assistant Doctors	3	5	4
3	Imaging Personnel	1	6	3
4	Laboratory Personnel	1	4	3
5	Nurses	1	3	3
6	Registration Secretaries	1	2	2

The lower and upper bounds for beds are given in Table VI.

Table VI: The lower and upper bounds for beds.

n	b_n	b_{ln}	b_{un}
1	Bed 1	6	8
2	Bed 2	10	20

4.1 Optimisation results

The objective of the optimisation model is to minimise the cost while considering the constraints. OptQuest within Arena was run with 1,000 simulations and 10 replications, and the optimal resource numbers were determined. Table VII presents the OptQuest results, showing the best resource combination selected to minimise the average patient waiting time. The best solution to reduce this time is to add resources for specific tasks while maintaining the current capacities of some resources.

Table VII: OptQuest optimal resource summary.

Decision variable	x_1	x_2	x_3	x_4	x_5	x_6
Optimal result	1	3	1	1	1	1

4.2 Comparison of the original and improved simulation models

In the final stage, the simulation model was recreated by modifying the relevant capacity values according to the resource combination recommended by the optimisation result, and this model was referred to as the improved simulation model. As a result of the optimisation, the number of assistant doctors increased from 2 to 3. While this slightly raises the cost, it leads to a significant reduction in waiting times and lengths of stay in the system. Additionally, beds that were already available but unused have been made available for use without contributing to the cost. Therefore, the number of beds is not included in the objective function. The number of Bed 2 has increased from 18 to 20. As a result, the average patient waiting times in the examination room have decreased. The improvements in waiting times after optimisation are presented in Table VIII.

Table VIII: Comparison of waiting times of bottlenecks before and after optimisation.

Average patient waiting time	**Before optimisation** (min)	**After optimisation** (min)	**Reduction**
Learning Patient History	6,44	1,45	77,48 %
Physical Examination	7,59	1,79	76,42 %
Post-Test Consultation with Doctor	7,62	1,42	81,36 %
Bed 1	6,33	1,18	81,36 %
Bed 2	31,8	7,95	75,00 %

As a result of the reduction in waiting times after the optimisation, the total length of stay in the ED for all patient groups has also decreased. The data show that optimisation has led to varying improvements across the groups. Details are provided in Table IX.

Table IX: Comparison of total length of stay in the ED before and after optimisation.

Group	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
İnitial *LOS*	10,9	20,8	45,3	122,7	347,6	684,7	1239,8	146,3	329	690,7	1234	3730,6
Optimise *LOS*	5,5	20,7	30,4	102	330,1	668,8	1205,5	111	286	636,1	1200,7	3612
Difference (%)	49,5	0,4	32,8	16,8	5	2,3	2,7	24,1	13	7,9	2,7	3,1

The comparison of the initial contact times with the doctor for Category 1 and Category 2 patients before and after optimisation is presented in Table X.

Table X: Comparison of initial contact time with the doctor before and after optimisation.

	Red	**Yellow**
Before optimisation	9,50	9,08
After optimisation	4,01	3,88
Decrease	57,79 %	57,27 %

Through various simulation trials, OptQuest aims to determine the optimal number of resources at the lowest cost by reducing patient waiting times below the desired levels, while adhering to the constraints specified in the mathematical model. In this regard, the different trial results provided by OptQuest are presented in Table XI. Additionally, scenarios involving various resource numbers suggested by OptQuest were run in the Arena simulation program, and the waiting times for Bed 1 (Q_1) and Bed 2 (Q_2) for patients were also determined and included in the Table XI.

Table XI: OptQuest scenario analysis.

Scenario	x_1	x_2	x_3	x_4	x_5	x_6	y_1	y_2	Q_1	Q_2	**Cost**
1.	1	3	1	1	1	1	6	20	1,18	7,95	24
2.	1	3	1	1	1	1	8	20	0,71	13,6	24
3.	2	3	1	1	1	1	8	20	0,53	3,94	25
4.	1	3	1	1	1	2	6	20	1,72	24,51	26
5.	1	3	1	1	1	2	7	20	0,99	15,83	26
6.	1	3	1	1	1	2	8	20	0,63	18,71	26
7.	1	3	1	2	1	1	6	20	1,18	7,95	27
8.	1	3	2	1	1	1	8	20	0,92	5,74	27
9.	2	3	2	1	1	1	6	20	1,30	9,83	28
10.	5	3	1	1	1	1	6	20	1,21	0,59	28

The change in the cost of the waiting times for Bed 1 and Bed 2 groups in the queue before and after optimisation is shown in Fig. 8. Although there is a slight increase in cost, the significant reduction in waiting times highlights the importance of optimisation. Similarly, in Fig. 9, it can be observed that the waiting times in the queue, for the post-test consultation with the doctor, physical examination, and learning of patient history processes have significantly decreased with optimisation.

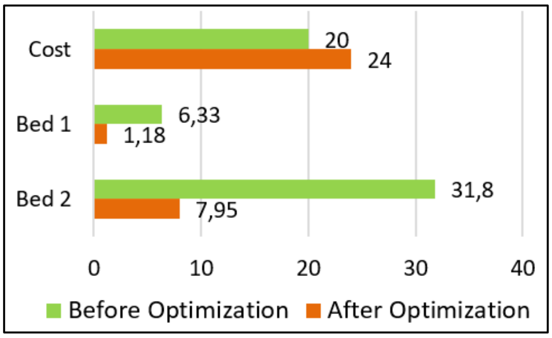

Figure 8: Cost-bed waiting time relationship.

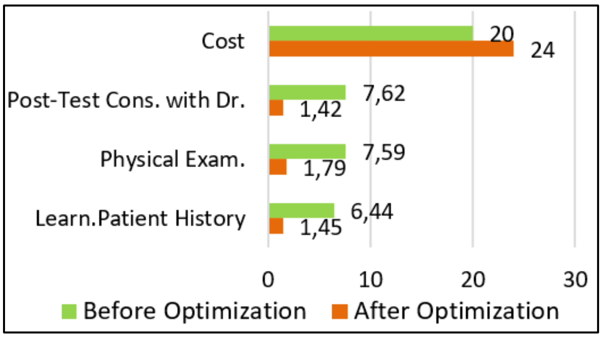

Figure 9: Cost-operation waiting time relationship.

In addition to optimisation efforts to address bottlenecks, various scenarios were developed. It has been determined that there is higher patient density during the second shift. Therefore, it was deemed more appropriate to increase the number of staff in the second shift. A total of 8 different scenarios were created by keeping the number of beds constant and varying the number of staff. These scenarios were designed in consultation with experts. The scenarios are presented in Table XII.

Table XII: Scenarios.

Personnel	**Scenario**	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
Assistant Doctor	1st Shift						2	2	2
	2nd Shift	4		4	4	4	4	4	4
Intern Doctor	2nd Shift		2	2				2	
Imaging Personnel	2nd Shift				2	2			2
Laboratory Personnel	2nd Shift					2			2

The values provided represent the waiting times for two beds across eight different scenarios. The results of the shift scenarios are presented in Table XIII. Q_1 represents the waiting time for Bed 1, and Q_2 represents the waiting time for Bed 2. Compared to the other scenarios, Scenario 3 has the lowest waiting times for both Bed 1 and Bed 2. Therefore, it can be considered the most suitable scenario for a system aiming to minimise bed waiting times.

Table XIII: Shift scenario analysis.

Scenario	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
Q_1	0,74	1,15	0,5	0,54	0,49	0,7	0,75	0,81
Q_2	11,6	4,65	1,54	7,92	4,26	11,1	2,04	13,82
Cost	26	24,5	26,5	27,5	29	24	24,5	27

4.3 Discussion

Nowadays, health-related studies are being conducted on different topics to improve health services (simulation of intensive care bed capacity [22], smart ambulance systems using the internet of things [23], the effect of medical logistics on health users [24] etc.)

The methodology that presented in the study can also be adapted to different healthcare units. Although patient arrival rates, resource numbers, treatment times differ, the general structure of the simulation model is suitable for adaptation to different models (intensive care units and family health centre). Also, the simulation model has some limitations and assumptions that may affect the generalizability of the results (constant resource number, unexpected patient arrivals and unpredictable external factors like natural disaster, epidemic disease, policy changes, etc.). In summary, the generalizability of the results depends on the compatibility of the assumptions with the real world. Using the proposed simulation model, ED managers can adapt resource number optimization to real life and observe improvements in patient flow or easily observe the effects of different resource number combinations on the system.

5. RESULTS

In the study, the simulation of the current system was first conducted to identify the constraints and bottlenecks in the system. To address these constraints and eliminate the bottlenecks, new simulation models were developed. Simulations allow for the analysis of different scenarios without cost by mimicking the operation of the real system and providing answers to "what-if" questions. The use of computer simulations in healthcare is increasingly becoming widespread as it helps improve decision-making processes and enhance operational efficiency. Compared to traditional statistical methods, simulations offer faster, more cost-effective, and more efficient solutions. In this study, the OptQuest optimisation tool in Arena software was used to optimise patient flow and service processes in the system. OptQuest has determined the optimal combination of resources while minimising patient waiting times. Based on the results obtained, the simulation model has been improved, and resource utilisation has been optimised.

As a result of the improvement model, significant reductions in average patient waiting times have been achieved. The waiting time in Bed 1 group decreased by 89.7 %, and in Bed 2 group, it decreased by 95.8 %. Additionally, the waiting time for a patient to provide a history decreased by 69.8 %, the waiting time for a physical examination decreased by 67.3 %, and the improvements have increased the efficiency of the ED, accelerated the treatment processes of patients, and provided higher quality service. Although there is a slight increase in the total cost of the ED with the OptQuest optimisation, the achieved efficiency and patient satisfaction balance out this cost. Improving these processes can provide long-term benefits by increasing customer satisfaction in the service sector.

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