Evaluation of the Patients' Queue Status at Emergency Department of Nemazee Hospital and How to Decrease It, 2014

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Abstract

Background: Patients, who seek care in emergency department, are waiting in queue and the health care provision in the department seems to be too overcrowded; the extended waiting time increases dissatisfaction and delays admission of new patients. In most of the hospitals considered to be overcrowded, the discharge rate of patients is managed by the use of "theory of queues". This study was done to observe waiting time of patients in emergency department by "queue theory analysis" and computer simulator in an Iranian hospital.

Methods: This is a cross-sectional study in which simulation software (Arena, version 14) was used to build the 8 models. They run in a period of one month. The input information for the models was extracted from the hospital database and through sampling. The objective of this study was to evaluate the response variables of "waiting time" and "number waiting" of each level.

Result: In Level 2A, with increased number of beds with 20 beds, the waiting time decreased to 0.45 minutes and the percentage of deaths declined to 26.2%, but the number of discharge from this level declined, too. In level 3 with increased number of beds 2 times, waiting time decreased to 74 minutes and the percentage of death declined to 3.7% but the number of discharge from this level to ICU declined, too.

Conclusion: This study showed the magnitude of ED overcrowding in Nemazee hospital. Increasing the bed capacity in the ED could reduce the waiting time in each part of ED.

Keywords: emergency department, bed capacity, waiting time, simulation, queuing theory

1. Introduction

One of the determinants of socio-economic development of a society is development of health services. Among the various sectors of health care providers, emergency department (ED) is one of the most important parts because it is providing fast medical services to patients in need and it can reduce mortality, morbidity and disability. Emergency ward has increased the chance of living for patients in need of urgent medical services in the first hours after an accident or a disease attack, known as "golden time", so lack of residents in the emergency department of educational hospital has a negative effect on making decisions and functioning and mostly. The emergency department has a great impact on other sectors and the quality of services represents the hospital status. Equipped and modern hospitals will not be known as qualified without the favorable conditions in the emergency department (Mojdeh et al., 2010; Cowan & Trzeciak, 2005).

Emergency Department (ED) triage visits patient according to the patient priority and illness severity. Emergency Departments (EDs) are specialized facilities for the acute care of patients who present without prior appointments. Patients arrive experiencing an array of complaints. Some of these complaints are life-threatening

and require immediate attention and the others are considered non-urgent and can wait until medical resources are available to be treated (Chonde et al., 2013). Appropriate services can contribute to promoting community health in proper time, and small errors in hospitals will lead to several problems (Smith & Varanelli, 2000; Haghighinejad et al., 2016).

One of the most important missions of emergency department free of bias based on socio-economic factors is providing public service and caring patients immediately. Doctors and medical staff must be present physically all hours a day and provide service to patients with acute and chronic diseases. Episodic, but frequent, overcrowding is a significant problem in academic, county, and private hospital EDs in urban and rural settings. Its causes are complex and multifactorial (Derlet, Richards, & Kravitz, 2001).

Crowding is a very common problem in ED, n prolonging the waiting times for patients. Extended waiting time increases dissatisfaction with healthcare systems, delays admission of new patients, and interferes with medical care to the admitted patients. Crowded EDs threaten the delivery of timely care, reduce the quality of care, and increase adverse and sometimes irreversible events (Mahmoodian, Eqtesadi, & Ghareghani, 2014). Emergency department (ED) overcrowding in the USA represents an emerging threat to the patient s' safety and could have a significant impact on the critically ill (Cowan & Trzeciak, 2005).

Waiting time is an important problem because of great demand and shortage of resources in all clinical fields, especially ED. One of the important solutions to reduction of costs and improvement of the quality of care is optimizing the patients' turnover and making a decision to eliminate bottlenecks and blocks in patient flow in ED (Alavi-Moghaddam et al., 2012).

All hospitals are considered to be overcrowded and discharge rate of patients is managed by use of "theory of queues" (Khanna et al., 2012). The more complicated models and systems need more close considerations and greater number of possible input elements; they are created by "queuing theory analysis" (Takakuwa, Shofer, & Abbuhl, 2007). The important parts of "queue systems" are people who are seeking services, entry process, queue discipline, service process and queue form. With this tool decision making can be done (Haghighinejad et al., 2016). Modeling and simulation studies of patient flows in healthcare systems have been reported for over a decade (White Jr., 2005).

Emergency department (ED) is a complicated model and can be changed by various variables over time. For this kind of model, simulation analysis is much more effective than analytical solutions. Several simulating software have been designed for this purpose which can simulate different models over time. These software can analyze "if-then" or (what-if) scenario in hospital emergency (Ferrin, Miller, & McBroom, 2007).

Shiraz is a city located in southern Iran with traditionally reference medical centers of the region. Emergency medicine specialists have been employed in major hospitals of the city since 2009, but the emergency medicine program has not yet been well-established. ED processes in this city have not been redefined according to the emergency medicine instructions (Mahmoodian, Eqtesadi, & Ghareghani, 2014).

The main reference hospital which delivers health services in southern provinces is Nemazi hospital in Shiraz, southern Iran. Beside other kinds of patients, critically ill patients, who cannot be managed in other centers, are referred to this hospital. Its emergency department works 24 hours a day. In spite of their physical space limitation, it must accept all patients indefinitely, regardless of their emergency or non-emergency conditions. Unlimited admission, high population coverage, and limited diagnostic and therapeutic facilities result in long queues which increase the patients' delay, so increasing the efficiency of the emergency department is a priority of health authorities.

One study in *University of Massachusetts* suggested that the simulation model in ED has value to the medical community and offers useful flexibility (Raunak et al., 2009). Clinical review on Cooper University Hospital, New Jersey, USA revealed that overcrowding in the ED could have a significant impact on the critically ill patients and identifies possible solutions focusing on ED based critical care (Cowan & Trzeciak, 2005).

Study of emergency department by Boyle et al. made a model and showed that crowding is caused by multiple factors and considered interventions at the level of individual hospital and a policy level (Boyle et al., 2012).

One of the examples of emergency simulators to reduce the patients' waiting time in the emergency room has been designed in Miami. Another model has been designed for estimating the maximum capacity of an emergency room and improving the patient flow in United States of America (Ferrin, Miller, & McBroom, 2007; Medeiros, Swenson, & DeFlitch, 2008).

In another study, Rossetti et al. used computer simulation to test ED attending physician and staff schedules and its impact on patients and resources were reviewed without disturbing the actual system (Rossetti, Trzcinski, &

Syverud, 1999).

Caban et al. present a multi-server two-stage tandem queueing model for a hospital emergency department (ED) triage and treatment process, using a Markov decision process formulation and sample path arguments to determine the optimal dynamic policy for the medical service provider (Zayas-Cabán et al., 2014).

Chonde et al. compared the capabilities of predicting the Emergency Severity Index (ESI) which is a 5-level acuity categorization system which aides in triage with other models in ED in Susquehanna Williamsport Hospital for 947 patients over a one month period in 2008. It contained the assigned ESI level, chief complaint, systolic blood pressure, pulse, respiration rate, and temperature, oxygen saturation level (SaO2), age, gender, and pain level. They showed that one model is recommended for considering speed, accuracy, data utilization, and flexibility (Chonde et al., 2013).

White et al. researched on the sources of data available to calibrate patient-flow simulation models, including time series for patient admission, discharge, diagnoses, length-of-stay, and inpatient census for emergency departments and hospitals. Specifically, they review the input analyses reported for various prior simulation studies, including data capture and technical difficulties in reducing data for model calibration. They also suggest alternative sources of data that could prove especially useful in simulation studies of mass ambulance diversions (White Jr., 2005).

Conelly et al. explored the potential of discrete event simulation (DES) methods to advance system-level investigation of emergency department (ED) operations. They described the development of Emergency Department Simulation (EDSIM), which is a new platform for computer simulation of ED activity at trauma center. They also demonstrated one potential application of EDSIM by using simulated ED activity to compare two patient triage methods (Connelly & Bair, 2004).

Also, Zilm et al. Explained the use of computer simulation modeling tool in three case-study, ambulatory care settings-a GI lab, holding beds for a cardiac catheterization laboratory, and in emergency services. These examples also illustrate the use of three software packages currently available: MedModel Simul8, and WITNESS (Zilm, Culp, & Dorney, 2003).

In a study, Laskowski et al. applied both agent-based models and queuing models to assess the patient access and patient flow in emergency departments, The models were developed independently, with a view to compare their suitability to emergency department simulation (Laskowski et al., 2009).

Moghaddam et al. used "ARENA" software for analysis, modeling, creating a simulation and improving the movement of patients in ED and revealed queuing theory analysis can improve movement and reduce the waiting times of patients (Alavi-Moghaddam et al., 2012).

Another study by Habibi and colleagues showed that the waiting time in the emergency service is too long and needs to be reviewed; the process of service delivery to patients in the emergency department and training programs for service providers are essential (Tabibi, Najafi, & Shoaie, 2009).

Mahmoodian et al. used triage systems to speed up identifying critically ill patients in EDs. Employment of triage scales in EDs has led to significant reduction in waiting times and improved patients satisfaction (Mahmoodian, Eqtesadi, & Ghareghani, 2014).

Haghighinejad et al. used Arena software for making three scenarios to simulate Faghihi hospital's ED overcrowding. Their study showed increasing the number of beds beside other capacities can decrease the queue and waiting time (Haghighinejad et al., 2016).

The aim of this study was to observe the current system of emergency department of Shiraz Nemazi hospital and compare different models made by their capacity to improve patient care and services. The objective of this study was to evaluate the response variables of "waiting time" and "number waiting" in queue in each level of ED as well as utilization of each server and offer a scenario to improve them. To improve these variables in ED, we increased the capacity of the servers so that the "number waiting" decreases.

2. Material Studied

This is a cross-sectional study in which simulation software (Arena, version 14) was used. This study was approved by the Ethics Committee of Shiraz University of Medical Sciences with ethical code: EC-92-6543

3. Area Description

When patients arrive in the emergency department (ED) and enter triage area, a triage provider (a nurse) takes a brief history and enters the patient's data in hospital database. Then, they send almost all patients to be visited by

a general physician in the screen ward. Patients are sent based on their conditions to "Level 1", "Level 2A", "Level 2B" and "Level 3" in the screen. As a rule, up to six hours decisions should be made for each patient in the emergency rooms. Critically ill patients who need CPR services are transferred to "Level 1" .Other patients who need mechanical ventilator and equipped bed with monitor are sent to "Level 2A". Patients with cardiac problems go to "Level 2B" and stable patients who need observational services are transferred to "Level 3". Other patients after receiving services may refer to hospital wards directly, or may be discharged from the hospital.

Hospital para-clinical services, such as laboratory, CT scan, MRI, sonography, radiology, endoscopy, echocardiography and electrocardiography (ECG) provide services to the majority of inpatients and ED patients.

4. Simulation Model

Arena (version 14), a discrete event simulation software, was used to simulate the emergency department queues. The flow diagram is shown in Figure 1.
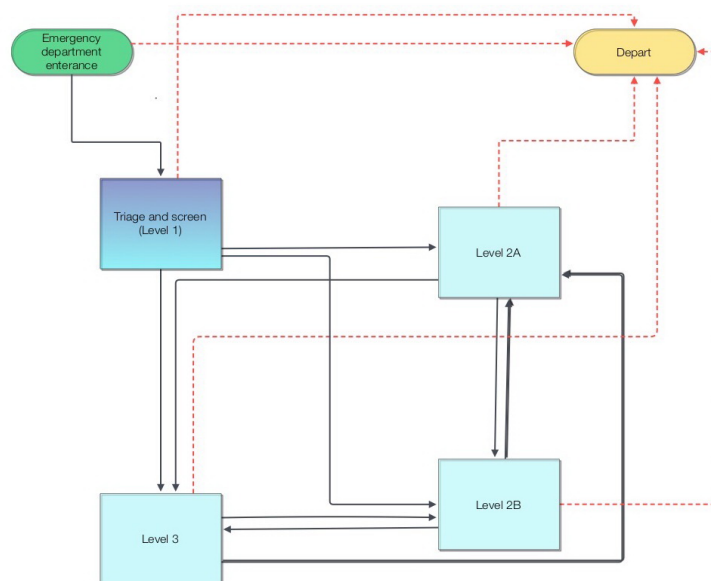

Figure 1. Patients flow diagram in emergency exit of nemazi hospital

It should be noted that any destination other than admission in the three levels mentioned (1, 2A, 2B, 3) is considered as "Exit" in the model. All models are designed by two variables, the time between two patient's arrival, and the length of stay in that part of ED. On the other hand, levels 2A, 2B, combination of Level 2A+2B and level 3 are designed with 2 models based on local definitions by the number of staff and equipment first with standard capacity and second with maximum capacity.

According to their equipment and staff in each level, standard number of beds defined. In overcrowded situations the numbers of beds increase without change in the staff and equipment, so models were made as a standard model and maximum model, respectively.

In the first level, the capacity of the server was designed in collaboration with 5 doctors against other models, because there is no clear definition of the number of beds. Due to lack of data, screen and triage ad CPR have been made in the one model (Figure 2).
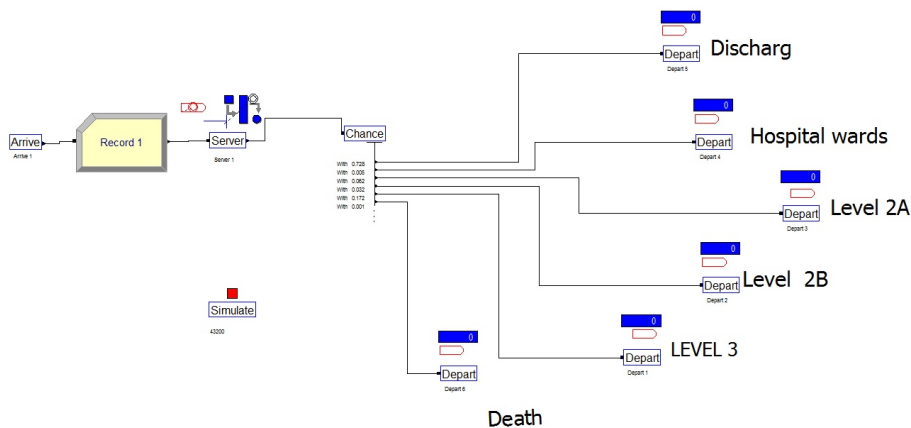
Figure 2. Level 1, screen and triage

The second level has 2 parts; one of them is "Acute 2A" in which critical ill patients are admitted and "Acute 2B". Simulation in "Acute 2A" was run by two capacities: first with standard capacity as 12 beds and another with maximum capacity as 32 beds (Figure 3).
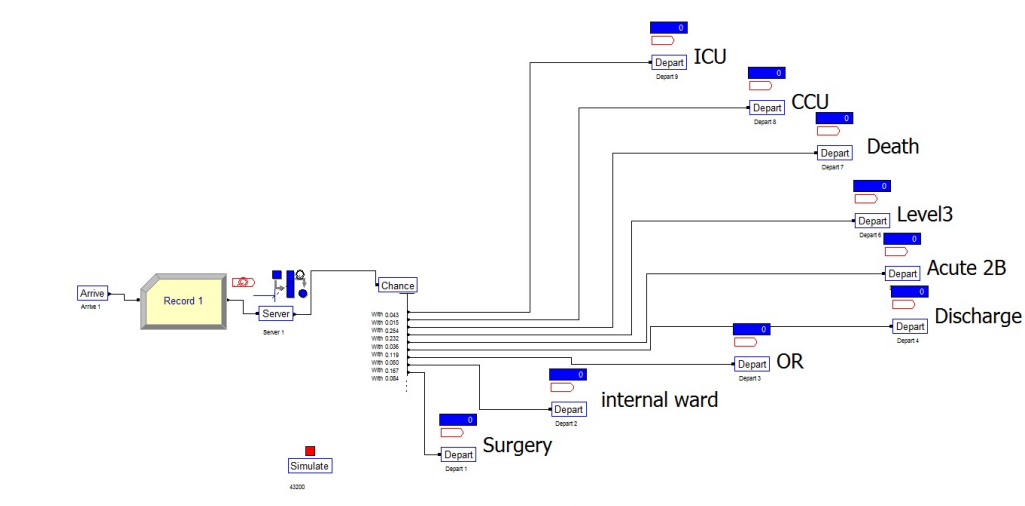

Figure 3. Acute 2A

Other parts of the second level is "Acute 2B", where patients with cardiovascular problems and in need of equipped bed with monitor are admitted and designed with 12 beds. The number of beds in this level precludes the queue and standard model is the current model; therefore, the maximum model was not made (Figure 4).
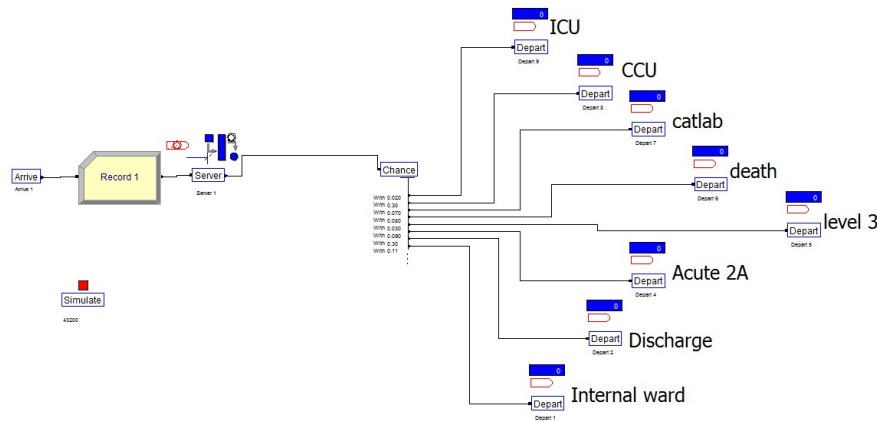
Figure 4. Acute 2B

"Acute 2A" and "Acute 2B" were combined and another model was made; this model was run with two capacities again. The standard model was simulated with 24 equipped beds and the maximum model was simulated with 44 beds (Figure 5). In this model, the time between 2 patients' arrival, time of service, and capacity of each model were combined to design a new model. Based on hospital database, most of the Exit from "Level 2B" were sent to "CCU" and "discharge" part, so in this new model, "Level 2A+2B" the percentage of all Exit of "Level 2B" was divided between "CCU" and "discharge" parts according to their probability and chance.
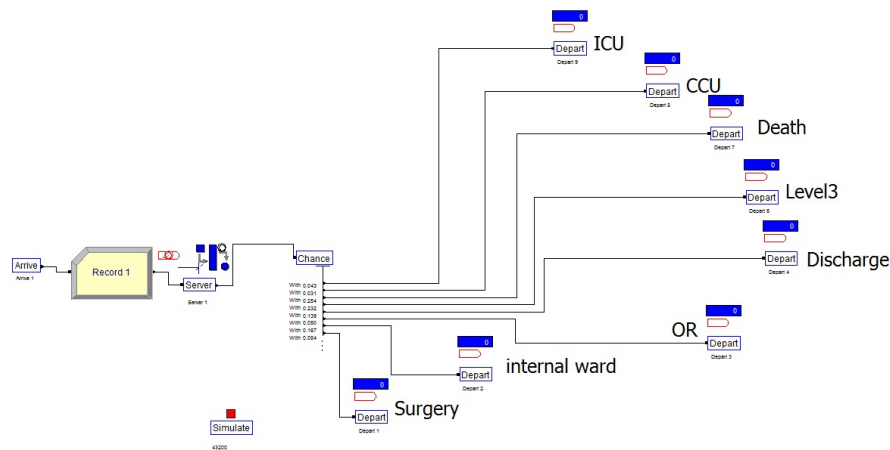

Figure 5. Level 2, Acute 2A+2B

In level 3, patients in a better condition or those who need conservative management were admitted. The model for this level was simulated in two conditions; the first was standard model with 40 beds, and the second was maximum model with 80 beds (Figure 6).
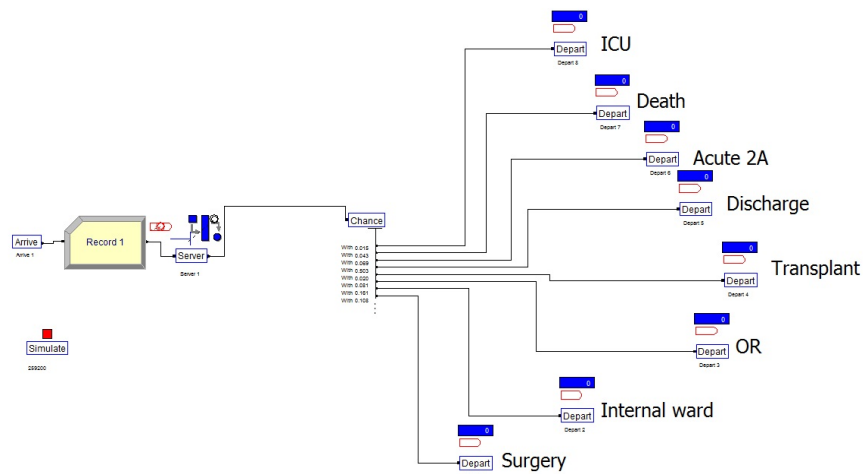
Figure 6. Level 3

4.1 Parameter and Variable Definition

The parameters required for designing the models included serving time, capacity of each server and the require time for transference between wards. Serving time was defined as "the time interval between entrance and exit from a ward". During admission in emergency department, the majority of patients required some diagnostic workups, such as radiography, laboratory test and sonography and many treatment services were required for all patients. All these serving times were included in the interval between entrance and exit from a ward.

The capacity of each clinical ward and room module was equivalent to the number of approved fixed beds in these sections, because the number of beds was designed based on the physical area, number of staff and devices, such as monitor, respiratory care support and so on. Except screen section where the capacity is determined by the number of doctors, the other part's capacity is determined by the number of beds.

In this study, response variables included: *Number Out*, *Waiting Time*, *Number Waiting*, *Instantaneous Utilization*, and *Number Busy*. *Number Out* is the average total number of entities for which Entity Statistics were recorded. *Waiting Time* is defined as the period of time since the patient enters a queue until the patient exits the queue. *Number Waiting* is the number of entities waiting in each queue. *Scheduled Utilization* is calculated by dividing the average *Number Busy* by the average *Number Scheduled*. *Number Busy*: This section reports the number of busy resource units. Number busy is a time persistent statistic. That is, the function will repeat itself throughout the simulation at all points of time and return the average value at the end of simulation (Swamynathan, 2008).

4.2 Data Collection

In this cross-sectional study, the data for the models were collected from both the hospital database and sampling. Sampling was necessary because the hospital database was inaccurate and imprecise in some areas, such as patients' length of stay. The arrival distribution function was fixed to one month's ED arrival data (from April 2014 to May 2014) extracted from the hospital database by input analysis of the arena software.

4.3 Sampling

A pilot study was carried out for calculating the serving time distribution function. The sample size for the pilot study was determined by a statistician and also by the ED experts' opinion. In ten random days of one month, 20 patients' serving time was collected from each level (80 samples totally). Standard deviation (SD) was calculated with confidence interval of 95% and precision or difference from mean (d) was calculated for each level separately. According to consulting statistician, the sample size was calculated using the Sample Size Calculator and PASS software.

The calculated sample sizes were as follows: screen (SD=81, d=13), sample size=152; Level 2A (SD=117, d=18.8), sample size=126; Level 2B (SD=146, d=23.4), sample size=96; Level 3 (SD=140, d=22.5), sample size=143. Therefore, overall 600 serving time samples were collected for the main study.

In a period of 1 month, data were collected in 4 parts of ED; they were "Level one", "Acute 2A" and "Acute 2B"

or level two, and "Level three". Then, they were coded. Each serving time include morning, evening and night added together. After that, we calculated the total entrance proportion distributed to each part of ED in a month. According to the sample size calculation, we selected pair patient to calculate the time between two entrances from each part of ED by "number generator software". Therefore, the software considered number 1 as the minimum and number of entries to each part of ED as maximum. The software selected each sample size randomly. Then, the pair's data from each shift of service were selected separately.

In this study, 8 models were designed with standard and maximum models. The simulation models were run for one day to show the "waiting time", "number of waiting" and "utility" of each part; the system started in an empty state and the ED was continuously operated 24 hours a day. They were run for 30 days again to show the percentile Exit of each model and to smooth the variability of ED patients' entry on different days of a week and different consecutive weeks. Because some small percentages, such as number of death, are not shown in a day and at least on month duration is needed to show their occurrence.

5. Result

The validity of the model was confirmed by comparison of simulation results with expert opinions and hospital actual data. This kind of comparison is the best way to validate simulating models (Sargent, 2004). Multiple replications was done for each model and due to similarity with one replication results, it is not reported.

5.1 Level 1, Screen and Triage

According to the existing model in ED, the patients were divided into inpatient and outpatient groups, after arriving in the triage section. Hospital recording data revealed that approximately 30% of the in-coming emergency patients required hospitalization and the rest of them (70%) didn't need to be admitted in the emergency department and were served as outpatient.

The simulation model was run for a period of 30 days. In this period, 16674 patients were discharged, and 16674 patients entered in a month; it means approximately 555.8 patients were sent out and 555.8 entered a day. The number of beds and staff cannot be changed in this model, so just the current situation is used for modeling. Other variables are shown in Table 1.

Table 1. Level 1, screen and triage results

variables	Number in	Number Out	Waiting Time(min)			Number Waiting			Utilization	Number busy
Simulation			Aver.	min	max	Aver.	min	max		
Standard model for a day doctors=5	555.8	555.8	6.31	0	80.8	2.43	0	78.0	0.97	5

Note. The model was run for a day.

For Exit distribution, about 15 patients died and 7382 were discharged; the other variables are shown in Table 2.

Table 2. Level 1 Exit distribution

EXIT	discharge	Hospital wards	Acute 2A	Acute 2B	Level 3	Death
Standard percentage (%) model for a month doctors=5	71.84	0.46	6.52	3.67	17.41	0.10

Note. The model was run for 30 days.

5.2 Acute 2A

At first, the model was run with the present capacity which means the number of beds in this area and it was run for a period of 30 days. In this period, 307 patients were sent out, and 689 patients entered in a month, i.e. 10 patients were out and 23 patients entered a day.

In maximum model scenario, the number of beds increased to 32 beds and these extra beds were added without any monitor or ventilator supplied. On average, no patient was waiting in the queue. Other variables are shown in Table 3.

Table 3. Level 2A results

Variables Simulation	Number in	Number Out	Waiting Time(min)			Number Waiting			Utilization	Number busy
			Aver.	min	max	Aver.	min	max		
Standard model for a day Bed=12	23	10	340.8	0	705.551	5.5	0	12	0.9782	11.7
scenario: decrease queue Beds=32 For a day (maximum)	22	22	0.45	0	6.94	0	0	0	0.848	27
Scenario: Decrease 29% of entrance come from "Level 3"	17	17	0.0	0	0.0	0.0	0	0	0.988	6

Note. The model was run for a day.

For Exit distribution, about 28.9 percent death occurred in the standard model and 26.2 percent in the maximum model; other variables are shown in Table 4.

Table 4. Level 2A exit distribution

EXIT	ICU	CCU	Death	Level 3	Level 2B	discharge	Operation room (OR)	Internal ward	surgery
Standard percentage (%) model for a month Bed=12	3.2	1.9	28.9	22.8	2.2	12.0	5.2	14.0	9.4
Scenario percentage (%): decreased queue Beds=32 For a month (maximum)	4.1	1.6	26.2	21.5	3.4	11.7	4.9	17.2	9.0

Note. The model was run for 30 days.

5.3 Acute 2B

The simulation model capacity was based on the number of beds in this area and it was run for a period of 30 days. In this period, 225 patients were out, and 228 entered a month, i.e. 7.5 patients were discharged and 7.6 entered a day. Other variables are shown in Table 5.

Table 5. Level 2B results

Variables Simulation	Number in	Number Out	Waiting Time(min)			Number Waiting			Utilization	Number busy
			Aver.	min	max	Aver.	min	max		
Standard model for a day Beds=12	7.6	7.5	19.1	0	703.1	0.1	0	4.0	0.62	7.4

Note. The model was run for a day.

For Exit distribution, about 4 patient's death and 19 patients' discharged, other variables have been shown in Table 6.

Table 6. Level 2B Exit distribution

EXIT	Discharge	Hospital wards	Acute 2A	Level 3	Death	ICU	CCU	Cath-lab
percentage (%) model for a month Bed=12	27.1	12	7.1	2.2	7.5	3.5	31.5	8.8

Note. The model was run for 30 days.

5.4 Total Level 2 (Acute 2A+Acute 2B)

The simulation model capacity was based on the number of beds in this area and it was run for a period of 30 days. In this period, 219 patients were out, and 277 entered a month, i.e. 7 patients were out and 9 entered a day. Other variables are shown in Table 7.

In maximum model scenario, the number of beds increased to 44 beds and these extra beds were added without any monitor or ventilator supplied; other variables are shown in Table 7.

Table 7. Level 2A+2B results

Variables	Number	Number	Waiting Time(min)			Number Waiting			Utilization	Number
Simulation	in	Out	Aver.	min	max	Aver.	min	max		busy
Standard model for a day Bed=24	9	7	53.20	0	207.8	0.36	0	1	0.8855	21.2
scenario: decreased queue Beds=44 for a day (maximum)	10	10	0.25	0	5.43	0	0	0	0.8006	35

Note. The model was run for a day.

For Exit distribution, about 52 patients died in the standard model and 75 in the maximum model; other variables are shown in Table 8.

Table 8. Level 2A+2B Exit distribution

EXIT	ICU	CCU	Death	Level 3	discharge	Operation room (OR)	Internal ward	surgery
standard model percentage (%) for a month Bed=24	3.6	2.2	23.7	23.2	13.6	5.4	17.3	10.5
scenario percentage (%): decreased queue Beds=44 For a month (maximum)	4	3.4	25.5	22.7	13.9	5.1	16.6	8.5

Note. The model was run for 30 days.

5.5 Level 3

The simulation model capacity was based on the number of beds in this area and it was run for a period of 30 days. In this period, 2463 patients were out, and 6011 entered in 180 days, i.e. 14 patients were out and 33

entered a day. Other variables are shown in Table 9.

In maximum model scenario, the number of beds increased to 80 beds and these extra beds were added with previous staff and no change occurred in the equipment; other variables are shown in Table 9.

Table 9. Level 3 results

Variables	Number in	Number Out	Waiting Time(min)			Number Waiting			Utilization	Number busy
Simulation			Aver.	min	max	Aver.	min	max		
Standard model for a day Bed=40	33	14	346.5	0	842.72	9.11	0	19	0.990	39.6
scenario: decreased queue Beds=80 for a day (maximum)	33	26	74	0	247.11	1.9	0	9	0.9284	74
scenario: decreased 16.3% of entrance from post-transplant ward	28.2	28.2	0.0	0	00.0	0.0	0	0	0.99	23

Note. The model was run for a day.

For Exit distribution, about 19 patients died in the standard model and 30 in the maximum model; other variables are shown in Table 10.

Table 10. Level 3 exit distribution

EXIT	ICU	Death	Acute 2A	discharge	Post-Transplant	Operation room (OR)	Internal ward	surgery
standard model percentage (%) for a month Bed=40	1.4	4.5	6.3	49.5	1.9	8.0	16.3	10.4
scenario percentage (%): decreased queue Beds=80 For a month (maximum)	1.3	3.7	7.4	50.1	2.1	8.3	15.7	11.1

Note. The model was run for 30 days.

6. Discussion

Queueing theory deals the most unpleasant experiences of life, waiting. And it is is quite common in many fields, The aim of all investigations in queueing theory is to get the main performance measures of the system which have several properties (distribution function, density function, mean, variance) of the following random variables: number of patient in the system, number of waiting patient, utilization of the server/s, response time of a patient, idle time of the server, busy time of a server (Sztrik, 2012).

So far, many studies have been carried out on reduction of patient's waiting queues in ED in hospitals worldwide and it is obvious that several factors affect this issue. The present study was designed on queuing theory to simulate the effects of increasing the number of beds and decreasing waiting time in an ED. Besides other factors, increasing the number of beds is one of solutions in ED to decrease the waiting time (Eggertson, 2004) and it is the most important variable in this study. As a result, if we intend to have no patient waiting in the queue for admission to the ED, we must increase the number of beds. But this is not a perfect solution unless other factors are considered as well. This change needs to be associated with appropriate increases in the numbers of physicians, staff, equipment and other necessities.

The result of this study showed increasing number of beds beside improving other factors such as staff training,

and dividing the patients properly and wisely in "Level one", and consider a separate and independent unit for patients who need conservative services can reduce "waiting time" and "number of waiting" in ED.

Before discussing the models, it must be noted that patients in the queue have received health care beyond the approved capacity by doctors and nurses who have no enough time to treat or take care of them. Also, they are confronted with the shortage of necessary equipped devices, such as ECG monitors, oxygen capsules, respirators, etc.

The standard model in the ED was simulated in 4 divided levels. It must be mentioned that most of the results obtained from the models and scenarios are simulated for a period of a day.

One of the most important causes of delay and patients' stay in the emergency department and crowding is lack of inpatient beds (Boyle et al., 2012; Bagust, Place, & Posnett, 1999).

On the other hand, all models were designed with maximum capacity too and run again for one day; their capacity is defined as increasing number of beds. In each model, the percentage of discharge was obtained for one month, so there might be more than one death a day and more time is needed to show this kind of result.

6.1 Level 1 (Triage and Screen)

Standard model (Tables 1, 2): Currently, the approved capacity of the triage is 5 doctors. It works with full capacity, i.e. 5 doctors working without rest daily. Most of the patients discharged from this model didn't require hospital services, as outpatient, and it means allocating a unit before this model to provide service to outpatient people can prevent them from going to ED and reduce the waiting queue.

6.2 Level 2A

Standard model (Tables 3, 4): In the standard model, on average, 6 patients were waiting in the queue for 340 minutes daily. However, this model worked with full staff and capacity and the utilization was 97% and all the 12 beds were involved. The number of occupied beds was 11.7 and it means that sometimes in a day one bed was empty. Exit was acceptable except that the number of death and that of discharge were less than other departments, like ICU and CCU. As to this model, two questions may spring to the mind: "Why was the number of patients' death so large?" And "Wasn't it better to send this critical patient to ICU or CCU before death?" On the other hand, the capacity of CCU and ICU was important and perhaps it means that the support level for this part did not work properly. The policy of hospital was important in this model too, and it was about the importance of ICU and CCU departments against the number of deaths in ED.

Maximum model (Tables 3, 4): In this model, the capacity increased to 32 beds from 12 beds, the number waiting and waiting time declined, the number of busy beds was 27 and it means 5 beds were not in use, but this model put pressure on the staff and equipped devices, because their number did not change.

It was also revealed in this model that increasing the number of beds had minimal effect on the number of patients who referred to ICU and CCU or died in this part of ED.

Comparison of these two models on "Level 2A" revealed that increasing the number of beds as a solution for reducing the waiting time (Haghighinejad et al., 2016) had an effect on reducing the number of deaths without any change in the number of staff or equipment and increased number of Exit from this part, but it reduced the number of overall discharge from the hospital.

29% of the admission in this ward come from level 3 monthly; it happens because of dividing the patient from level 1 is done with poor accuracy or their condition become worse during hospitalization, with a decrease in this percentage, the "number of waiting" and "waiting time" declines to zero (Table 3).

6.3 Acute 2B

Standard model (Tables 5, 6): In this model, most of the Exit cases were sent to CCU and discharged. The capacity was 12 and utilization was approximately 11; it means that sometimes one bed might be empty during a few days. As mentioned before, "Level 2A" was for critically ill patients and referral from this part of ED to "Level 2A" means that misdiagnosis happened or "Level 2A" was full and could not admit extra-patients. In this part of ED, just a standard model was designed.

6.4 Acute 2A+2B

Standard model (Tables 7, 8): The result of this model revealed that if "Level 2A" worked separately, waiting time was approximately 5 hours, but if "Level 2B" was added to "Level 2A", it decreased to 53 minutes without adding any device or monitor or staff, etc. Waiting number was 0.36 and it means on average, one patient was waiting every 2 days. "Number busy" revealed that sometimes in a day three beds may be empty. Death reached

its highest percentage according to this model.

Maximum model: (Tables 7, 8): In this model, the capacity increased to 44 beds from 24 beds, but the number of patients who referred to ICU, CCU or died in this part of ED did not decline again, like discussion in level 3, maximum model.

Comparison of this two model revealed that increasing the number of beds as a solution for reducing the waiting time (Haghighinejad et al., 2016) without any change in the number of staff or equipment had a reverse effect on the number of deaths, but it could increase the number of Exit from this part and number of Exit to ICU and CCU and increase the number of overall discharge from hospital.

6.5 Level 3

Standard model (Tables 9, 10): Exit to ICU and 'Level 2A" and the number of death were not suitable for this part of ED which is designed for stable patients and those in good condition. Two reasons could explain this; it might be the mistake of screen department which is responsible for diagnosing and distributing ill patients appropriately, or on the other hand, "Level 2A" and "2B" were full and borrowed level 3 beds. So, the number of poor condition patients increased in level 3 which is not proper for this kind of patients. Thus, as mentioned, wrong patients entered level 3.

Another result of this study was Exit to "Post-Transplant" ward for approximately two percent. Another problem in hospital leads to overcrowding in ED; there was no suitable place for follow up of post-transplant patients, and they were admitted to "Level 3" of ED for several hours to 10 days to get services and prepare for transfer to the post-transplant ward.

Waiting time in this model remained beyond the standard definition and "decision making indicator" that is maximum 6 hours (Hoot & Aronsky 2008). The standard definition of length of stay (LOS) and "decision making indicator" that was maximum 6 hours. The LOS in two hospital emergency rooms was about 283 minutes (Hoot & Aronsky 2008).

Maximum model (Tables 9, 10): In this model, the number of beds increased to 80 beds, discharge cases increased to 26 and just two people waited in queue for 74 minutes a day. Number busy was 74 and it means that 6 beds were empty during a day and utility was 92%. Its result showed that an increase in the capacity to maximum could not eliminate the queue. And in this model, all other factors such as staff, equipped bed, monitor, etc. did not change and stresses to all clients and pressure to all capacities were inevitable. It seems that to eliminate these queues in this part of ED, we must have another level 3 with the same staff and devices and beds. The Exit to ICU and "Acute 2A" and death were not suitable in this part again. The Exit to post-transplant ward was approximately 2% again.

Comparison of these two models revealed that increasing the number of beds as a solution of reducing waiting time (Haghighinejad et al., 2016) without any change in the number of staff or equipment had an effect on reducing the number of death and increasing the number of Exit from this ward and from hospital totaly. But referral to "Level 2A" increased with increasing number of beds.

According to the definition of the American College of Emergency Physicians, "crowding occurs when the identified need for emergency services exceeds the available resources for patients care in the emergency department, hospital or both" (Pines et al., 2011).

ED crowding is a recognized problem across the world (Boyle et al., 2012) and the current policy is to develop ED in the countries with the purpose of increasing the ED's capacities (Eggertson, 2004). But how much development is needed to improve the capacity and eliminate overcrowding? Predicting the required beds in this study was one of the best ways to solve overcrowding.

This model could not eliminate overcrowding with increase in the number of beds and it seems another criterion like increase in other ED's facilities is needed more than beds, because as mentioned previously overcrowding happens due to lack of resources (Pines et al., 2011).

Comparison of these two models revealed that increase in the number of beds as a solution of reducing waiting time (Haghighinejad et al., 2016) without any change in the number of staff or equipment had an effect on increase in the number of Exit from ED. Another study revealed that one of the solutions for ED's crowding is adding a holding unit for non-critically ill patients (Pines et al., 2011). To manage overcrowding in ED in Canada, the current policies considered are increasing the number of critically ill patients' beds based on several variables such as population size, demographic conditions, patients' vigilance and technology (Bagust, Place, & Posnett, 1999).

16% of admissions in this ward come from post-transplant ward monthly, it happens because a separate ward or unit is not used for these patients who don't need emergency services, with a decrease in this percentage, the "number of waiting" and "waiting time" declines to zero (Table 9).

At the end, we must mention that there is not a good source of data for following patient from ward to ward, and recording time of waiting in queue in our hospital; on the other hand, although the IT infrastructure in this hospital is more reliable than collecting data manually, availability of original software such as "Arena stimulating software" in our country is another limitation of this study.

6.6 Suggesting Solutions

Four strategies are recommended to manage the effects of increased acceptance in ED: creating an observation unit, avoidance of admitting too many patients, better use of the existing resources, and possibility of earlier discharge (Bagust, Place, & Posnett, 1999; Haghighinejad et al., 2016).

Decreasing the arrival rate can be helpful. To avoid excessive admission, some policies should be developed in line with the goals in Iran. The hospitals should have permission to accept patients according to their capacity in order to meet the needs of patients. Currently, policies force the ED to accept the patients according to the community demand not to the ability of responding. Another problem is that the emergency transportation services have to transfer the patients only to public hospitals.These policies cause ED overcrowding and have no effect but increasing *waiting time*, medical error, and exhaustion of the personnel, patients and physicians. The emergency transportation centers should be able to divide the patients between both private and public hospitals according to their affordability and requests. However, it is important to improve the private hospitals' facilities, and their practical and scientific level (Tabibi, Najafi, & Shoaie, 2009).

Observing the unit would decrease the load of acute care hospital beds and home care can keep chronically ill patients out of ED (Eggertson, 2004). Providing such facilities in addition to reducing hospital *waiting time* imposes less cost on both the patients and health care system.

Better use of the existing resources to speed up provision of services to the patients is possible by using experienced personnel and physicians, accuracy of decision-making, performance, and ability to work in the stressful and high-speed environment of ED. Unexperienced nurses and physicians in an ED can congest the system, increase medical error, and waste resources (Khare et al., 2009). Earlier discharge can also be effective but has some long term limitations.

7. Conclusions

This study showed the significance of ED overcrowding in this hospital. Increasing the bed capacity in the ED could reduce waiting time in each part of ED. This included bed capacity requirement for both critically ill and less critically ill patients. The number of patients who refer to ICU, CCU or die in ED did not decline and increasing the number of beds must be considered beside other improvements in staff, equipment and services.

Discharge of patients to "ICU" and 'Level 2A" and the number of deaths were not suitable for level 3, which is designed for stable patients. Two reasons could explain this model; it might be the mistake of screen ward to diagnose appropriately, or maybe "Level 2A" and "2B" were full and borrowed beds in level 3. Future studies should focus on the bed requirement for critical care and holding units separately

Ethical Issues

Approval for this study was given by the Ethics Committee of Shiraz University of Medical Sciences with ethical code: EC-92-6543.

Competing Interests Statement

The authors declare that there is no conflict of interests regarding the publication of this paper.

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