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STUDY ON THE EFFECT OF DIFFERENT ARRIVAL PATTERNS ON AN EMERGENCY DEPARTMENT'S CAPACITY USING DISCRETE EVENT SIMULATION

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The increased volume in demand for medical assistance, and the severity and diversity of injuries sustained among those affected by a disaster, can easily overwhelm limited resources available at hospital emergency departments (EDs) when providing care to victims affected by a disaster. To meet this sudden surge in demand involving huge uncertainties and complexities, EDs need to be better prepared and more efficient. This paper looks at the creation and use of discrete event simulation modeling using ARENA 10.0 software. In this paper, an attempt is made to show how the different arrival patterns and time durations in which victims are arriving affect on ED's ability to treat patients during a conventional terror disaster event. The disaster event scenario includes open-air disaster environment and confined or closed-space disaster environment. It also shows how the model can be used to estimate additional resources that would be required to accommodate additional patients within the ED.

Keywords: Patients arrival patterns, Emergency department preparedness, Discrete event simulation

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1. INTRODUCTION

Disasters can be natural or man-made. Any disaster has the capability to overwhelm a limited amount of medical resources available for treatment of victims affected by the disaster. The Virginia Office of Emergency Medical Services defines a disaster as an "incident that generates more patients than available resources can manage during routine procedures" (Green, 2000). This definition will be used in this research to define a mass-casualty disaster. Emergency departments (EDs) face significant surges in daily demand. However, the surge during a disaster event is quite different than that seen during daily operations. Apart from the huge increase in volume of patients seeking medical assistance, the severity and diversity of injuries, which are likely not seen during daily operations by an emergency department, also add to the surge in demand during a disaster. In order to cater to such a huge increase in demand for medical resources, hospital facilities can expand their capacity by mobilizing physical and personnel resources within the hospital to cater to the increase in demand. Most hospital EDs have emergency response plans in place, which are activated during such an event.

Hospitals need to be prepared to cater to huge increases in demand involving such huge uncertainties. However, one of the most important and often missed factors affecting an ED's preparedness and ability to provide timely treatment to all victims affected by the disaster is the immediacy with which such disasters impact the ED. The time frame for dealing with disaster places huge demands on the ED during such an event. In other words, time of arrival of the first victim and duration over which the victims keep arriving at the ED seeking medical assistance bears relevance in planning for such events.

2. OBJECTIVE

The main objective of the research is to study the effect of different arrival patterns and the time duration over which disaster-affected victims keep arriving at the ED seeking medical assistance. We will look at an ED's capacity and ability to treat patients in a timely manner without having any mortality and morbidity associated with the disaster-affected victims. The disaster under consideration is a conventional terror disaster event, which includes an open-air disaster environment (that take place in open areas like market place, stadium, open parking lot, etc.) as well as a confined also often called closed-space disaster event (that occur in closed/confined places like trains, buses, cars, etc.). One of the other objectives of this research is to study and analyze patient flow and injuries associated with a conventional terror disaster event.

3. LITERATURE REVIEW

A variety of methods for modeling hospital operations are found in the literature. A detailed review of use of linear programming, dynamic programming, queuing theory, control theory, and dynamics in modeling hospital operations is available by Paul et al., (2006). This research work uses discrete event simulation to model an emergency department's operations, and hence, the literature supporting the modeling of various operations within the hospital using discrete event simulation as a modeling technique will only be summarized.

Cote, (1999) developed a simulation model for an outpatient clinic to study the influence of examination room capacity and patient flow on four performance measures: 1) room utilization, 2) room queue length, 3) examination room occupancy, and 4) patient flow time. The model was affected by arrival rate only.

A simulation modeling technique was used to estimate the maximum possible demand increment in the emergency department of a private hospital in Chile. In this study, Baesler et al., (2003) used the model to create a curve for predicting the behavior of a variable patient's time in the system and estimate the maximum possible demand the system can absorb. They used the design of experiments principle to define the minimum number of physical and human resources that would be required to serve this increase in demand. While the above simulation studies were conducted for a particular hospital during normal operations, Hirshberg et al., (1999, 2005) developed a simulation model to study surgical resource utilization and utilization of other facilities within the hospital during an urban terror event. The model was based upon the hospital disaster response plan for a 1400-bed hospital in Israel. They modeled the arrivals as a Poisson process, which usually is not the kind of distribution that follows patient arrivals during a disaster. Patvivatsiri, (2006) and Patvivatsiri et al., (2007) on the other hand, used a simulation modeling technique to evaluate the preparedness of an emergency department of a particular hospital in Texas during a CBRNE event. Paul et al., (2006) used a simulation modeling technique along with transient modeling to estimate real-time capacity of a hospital. An attempt to estimate real-time arrival of patients to the hospital was also made. The model developed here was for an earthquake situation.

Thus, very little work seems to have been done on studying the impact of different arrival patterns and time durations on an ED's capacity to treat patients during a conventional attack. This work seems to be the first of its kind in this approach.

4. METHODOLOGY

In order to study the objectives of this work, a discrete event simulation model was built using ARENA 10.0 simulation software. The model focuses on and models operations within the emergency department, x-ray, computed tomography (CT-Scan), and operating rooms (ORs). The intensive care unit (ICU) and inpatient beds are not included in the scope of the model. Values used in the model for service / treatment times within different treatment areas; probabilistic routings within various departments considered in the model; and expiration time / survivability time, which is defined as the time for which a patient can wait before treatment, based upon severity type, are based upon information provided from a level III trauma center in Topeka, Kansas.

4.1 Modeling Assumptions

1. Non-disaster related patient volumes will be the same that the emergency department of a level III trauma center experiences during a normal day.
2. Patient types classified in the model will retain their attributes throughout the model.
3. Level of care for critical / serious patients follows the standard level of care given to these patients during routine operations.
4. The model assumes that non-disaster patients of severity level 2 and severity level 3 will be taken into the facility for treatment only if the time until the first resource available for their treatment is less than the expiration time assigned to them in the model.
5. The model assumes that treatment priority is given to disaster-affected patients over non-disaster-affected patients.
6. Service times are modeled as a triangular distribution since the exact service times were not available. Expiration times are also modeled as a triangular distribution to allow the range of minimum, maximum, and most likely duration for expiration time so that different times are allocated to every patient created in the model.
7. Travel times associated with the movement of patients between various departments is modeled as a uniform distribution, allowing minimum and maximum travel times between the departments.
8. The model assumes that the CT-scan facility will be reserved for use of severity level 3 patients and x-ray for severity level 2 patients.

Injuries resulting from a disaster are traumatic in nature, and routing of patients between various departments is based upon detailed injury type. The disaster under consideration in this research is a conventional terrorist bombing attack. Patients were classified into eight different groups based upon the injury type listed by Arnold et al., (2003). Table 1 shows the adjusted percentage distribution based upon information available from the abovementioned paper.

Table 1. Injury distributions by disaster event environment type used in the model (Source: Modified from Arnold et al., 2003)

	Confined Space (%)	Open Air (%)	Patient Group
Head injury (%)	2	1	Type 1
Respiratory distress (%)	16	4	Type 2
Gastrointestinal (%)	8	2	Type 3
Penetrating eye (%)	1	1	Type 4
TM rupture (%)	18	1	Type 5
Penetrating soft tissue (%)	30	85	Type 6
Orthopedic (%)	12	5	Type 7
Burn (%)	13	1	Type 8
Total	100	100	

Three types of severity levels were defined in the model. Table 2 summarizes the definition for each of the severity levels. Patient routings within the hospital facility are based upon treatment procedures mentioned in Greenberg's Text-Atlas of Emergency Medicine for all categories except the first three types of injuries (Greenberg, 2005). Treatment algorithms given in Disaster Medicine by Hogan and Burstein (2007) were used to determine the routing within the hospital facility for the first three injury types.

Patient type 1 through type 5 are assigned severity level 3 in the model as the patients suffering from these injuries were found to be closest to the blast point and suffered from serious injuries. Similarly, patient type 6 through 8 are assigned severity level 2 and patient type 9, which was created separately in the model and called the walking wounded, was are assigned level 1 severity as they are the ones who suffer from minor lacerations, sprains, strains, etc.

Table 2. Severity level of injury (Source: Emergency War Surgery: Third United States Revision, 2004)

Severity Level of Injury	Description	Patient Group
Level 1	Patients with minor injuries who are capable of self transporting themselves to the hospital; these patients require basic medical and do not require hospitalization.	Walking wounded; minimally injured patients Patient Group 9
Level 2	Injuries requiring a greater degree of medical care and hospitalization, but not expected to progress to a life-threatening status.	Moderately injured patients. Patient group 6 through 8
Level 3	Injuries that pose immediate life-threatening conditions if not treated adequately and expeditiously within a few hours.	Severely injured patients Patient group 1 through 5

4.2 Model Design

The simulation model assumes that from the triage station, depending upon injury severity, patients assigned to severity level 3 are sent to the most highly equipped treatment area within the ED, which is the shock room area (also called trauma room area or resuscitation bay). The model assumes that initially four; fully equipped trauma rooms are available for treatment of patients coming to this area. This area is initially assumed to be staffed with two trauma teams, with each of the teams consisting of one trauma surgeon, one trauma nurse, and one registered nurse. The model further assumes that until a complete trauma team and trauma bed is available for the patient's treatment, the patient will experience wait time. Patients with injury severity at level 2 are sent to the standard ED bed area, which initially consists of 15 ED beds. This area is staffed by 10 registered nurses and two emergency physicians. The model assumes that patients coming into this treatment area will first wait in a queue for a bed, and then upon seizing a bed will wait in a common queue for the first available medical personnel to treat them. Medical personnel in this area could either be a nurse or a physician as the model assumes that nurses and physicians have the same level of expertise here to treat the patient.

Patients with minimal injuries like minor cuts, pain, strains, and stress are sent to an area other than the ED, which in this case is assumed to be the outpatient department (OPD). This area is initially staffed with six registered nurses. Table 3 gives a summary of initially available resources in the different treatment areas. The model assumes that the two available CT-scan machines are reserved for use with patients who are treated in the trauma room's area, while the four available x-ray machines are reserved for use by patients treated in the standard ED beds area.

Due to the huge volume of patients coming in a short period of time, it is likely they will experience wait-time. But each of the patients arriving will have a wait time tolerance that is the maximum amount of time they can wait before seeing the first medical personnel on a treatment team and getting treated by him/her, which in this work is defined as expiration time / survivability time. The waiting-time tolerance will, however, have different meanings for patients of different severity.

Table 3. Resource profile for initial runs

ED Treatment Areas	Resources	Initially Available Capacity
Trauma rooms area for severity level 3 patients	Trauma beds Trauma surgeon Trauma nurse Registered nurse	4 2 2 2
ED standard beds area for severity level 2 patients	ED beds Emergency physician Registered nurse	15 2 10
OPD area for severity level 1 patients	Registered nurse	6

For patients with injury severity level 3, if the maximum time which they can wait until first seen by medical personnel exceeds their tolerance limit, then these patients will be dying and can be termed as "critical expire." Statistics on critical expire count are captured in the model. For patients with injury severity level 2, if wait-time tolerance exceeds the time until first seen, then they can be counted or termed as "left without being seen (LWBS)" and the statistics on the same are captured in the model. The model assigns the expiration time attribute to patients with severity levels 2 and 3. The value assigned to these patients follows the triangular distribution. Patients with level 1 severity are not assigned any expiration time as their injuries are not going to advance to a life-threatening stage at any point of time.

The disaster also does not relive the ED of treating patients who are not affected by the disaster. The model assumes that non-disaster patients of severity level 2 and severity level 3 will be taken into the facility for treatment only if the time until the first resource available for their treatment is less than the expiration time assigned to them in the model. For those who are not taken into the facility, the model captures these counts as patients who are diverted to other facilities for treatment and are termed as "everyday patients diverted."

Arrivals

The process begins when patients arrive at the hospital. The model assumes that the disaster victims arrive in one of the two ways: walk-in and ambulance. Thus, two different CREATE blocks exists for generating each of the two types of arrival in the model. In disasters, patient arrivals are highly dynamic, and the arrival rate of patients changes continuously. It is difficult to estimate the exact arrival of patients to the hospital. A surge in patient volume occurs every few hours following a disaster (Halpern et al., 2003). This volume of patients then fades away over the later hours and eventually calms down. Although this general trend can be found in many disasters, the exact shape of arrivals varies from disaster to disaster. The amount of delay the arrivals pose on the system is an important factor, as it determines the immediacy with which such events affect critical resources of the hospital.

Considering the aforementioned issues, arrivals were modeled as exponential distribution with a mean of λ, which follows a gamma distribution with shape parameter α and scale parameter β, which is expressed as EXPO (GAMMA (β, α)). Gamma distribution was selected as it offers the flexibility of having different shapes of distribution by changing the scale and the shape parameter. Thus, the CREATE block generating "walk-in" and the "ambulance arrivals" assumes to follow an exponential distribution with mean λ, which follows a gamma distribution with scale and shape parameter.

Experience has shown that early victims arrive 15 to 30 minutes post event, and later victims greater than 30 minutes (Frenn and Whitely, 2004). The arrival expression for "walking wounded" is fixed throughout the experiments to EXPO (GAMMA (25, 1.25)), which represents the expected delay imposed by these patients. Gamma parameters used in the above expression are obtained from Sullivan (2008), which is in line with observations made by Frenn and Whitely, (2004) and Bohonos and Hogan, (1999). The focus of this work is to analyze the impact of different arrival patterns of ambulance arrivals which, constitute victims of severity 2 and 3, thus the expression used in the CREATE block was a variable.

The occurrence of a disaster does not relieve the hospital from treating "everyday emergency" patients. Thus, another CREATE block is used to create the everyday emergency patients. It is assumed throughout the simulation that everyday emergency patients follow a constant arrival rate and follow a Poisson distribution. These entities are created according to the expression EXPO (time between arrivals). This expression needs to be initialized by the user before the simulation is run. The value in this expression should be assigned based on historic data and can be calculated by taking 1440 (the number of minutes in a day) and dividing it by the average number of patients arriving at the hospital each day. This gives the average number of minutes between each arrival. Daily patient arrival statistics obtained from Stormont Vail Hospital, a level III trauma center in Topeka, Kansas, is used to calculate average patient arrival rates for running the model. The hospital has an average of 132 patients per day. Thus, the arrival process is modeled as an exponential with a mean of 10.99 minutes. The percentage distribution of severity types of normal everyday patients was assigned based upon the data available from the ED. Table 4 summarizes the percentage distribution based upon severity types for the normal, everyday emergency patients used in the model.

Table 4. Percentage distribution of severity type for normal, everyday emergency patients

Patient Type	Percent Distribution
Severity level 1	30
Severity level 2	65
Severity level 3	5

5. REAL-LIFE EXAMPLES

Once the model was built, verified, and validated, it was used to run experiments with the input parameters. The input parameter studied was the arrival distribution of victims arriving by ambulance. It is assumed that disaster-affected patients with injury severity levels 2 and 3 are the ones who will arrive by ambulance, and those with level 1 severity will be termed as walking-wounded.

Apart from the dynamic arrival of patients to the ED during the disaster, another important factor which affects performance of the ED is the duration for which the ED is under the impact of the disaster. Studies have demonstrated that in the first 12 hours post incident; half of the victims seek emergency department treatment, thus directly affecting utilization rates and demand for ED capacity during these mass casualty incidents (Kalemoglu, 2005). In the 1993 World Trade Center event, only 50% of injured survivors arrived at the EDs within 3.5 hours of the blast (Arnold, 2004). In 2001 World Trade Center event, injured survivors with minor injuries continued to arrive at EDs more than 24 hours after the attack (Arnold, 2004). Thus, from above information, we can conclude that for any disaster, the first 24 hours are of critical nature during disasters affecting an ED's capacity to treat patients, as almost all victims will be requiring treatment within the first day.

To perform the study, various combinations of α and β parameters were chosen to see which of the arrival patterns affected the key performance parameters of interest. In order to study an ED's capacity under different arrival patterns and time durations, experiments were run with 14 combinations of the shape and scale parameter for four different time periods. The combinations of shape and scale parameter used for the experiment are shown in Table 5. All 14 combinations were run for simulation run times of six hrs, 12 hrs, 18 hrs, and 24 hrs to show the effect of arrival pattern and time duration on an ED's capacity.

Parameter α has the greatest effect on the shape of the distribution. As the value of α increase's in limit, the distribution approaches normal distribution. Scale parameter β adjusts the mean of gamma. The larger the scale parameter, the higher the variance and the bigger the spread of the distribution across the horizontal axis.

5.1 Experiment 1

Objective

To study the effect of different arrival patterns for different simulation run times of six hours, 12 hours, 18 hours, and 24 hours.

Methodology
The simulation model was run with all 14 combinations listed in Table 5. Each combination was run for simulation run times of six hours, 12 hours, 18 hours, and 24 hours. This resulted in 14 x 4 = 56 combinations. Each of these combinations was run for 30 replications. The aim was to see, out of the 56 combinations, which resulted in zero critical expires, zero LWBS, and zero patients diverted. The system was initialized by inputting the resource capacities mentioned in Table 3.
Results and Discussion
It was found that for the six hours of simulation run time, distributions with parameters (3, 4), (3, 3), (3, 2), (2, 4), (2, 3), (4, 2), and (2, 2) resulted in zero critical expires, zero LWBS, and zero patients diverted. Distributions (3, 1), (1, 2), (0.5, 2), (2, 1), (1, 4), (1, 3), and (1, 1) resulted in greater than zero critical expires, LWBS, and patients diverted. When the same model was run for a simulation run time of 12 hours, it was found that distributions (2, 2) and (2, 3), which met the criteria for six-hour simulation run times did not meet the criteria when run time was extended to 12 hours. Similarly, the model was run for an 18 hour run length and a 24 hour run length. It was found that distribution (3, 2), which met the criteria in six- and 12- hours run times did not meet the 18- and 24-hour simulation run times. Thus, it was found that distributions (3, 4), (3, 3), (2, 4), and (4, 2) were the only distributions which resulted in zero critical expires, zero LWBS, and zero patients diverted under all simulation run lengths. Thus, it can be concluded that these distributions did not affect the ED's ability and capacity to treat patients affected by the disaster, coming in under these arrival patterns. Further, it can be concluded that the shape of the arrival distribution affects the ED's capability to treat patients and bears relevance in planning.

Table 5. Combinations of scale parameter and shape parameter used in the experiment to model ambulance arrivals

		(β)	(α)	Mean =(α) (β)	Variance = (α) (β)^2
Set 1	Input 1	3	4	12	36
	Input 2	3	3	9	27
	Input 3	3	2	6	18
	Input 4	3	1	3	9
Set 2	Input 5	2	4	8	16
	Input 6	2	3	6	12
	Input 7	2	1	2	4
Set 3	Input 8	1	4	4	4
	Input 9	1	3	3	3
	Input 10	1	1	1	1
Set 4	Input 11	4	2	8	32
	Input 12	2	2	4	8
	Input 13	1	2	2	2
	Input 14	0.5	2	1	0.5

5.2 Experiment 2
Objective
To estimate the number of additional resources that would be required to get the critical expires count, LWBS, and patients diverted to zero.
Methodology
Out of all distributions which resulted in greater than zero critical expires, LWBS, and patients diverted, distribution (1, 2) was selected to show how the model can be useful to reallocate and estimate the additional resources that would be required to get zero critical expires, zero LWBS, and zero patients diverted under this arrival distribution. In experiment 1, it was found that nurse utilization in the OPD area was just about 23%. This means there was an excess capacity in this area and registered nurses were under-utilized, while in the trauma room area, under this distribution there were three critical expires and there was at least one LWBS patient in the standard ED beds area. Thus, in order to increase utilization in the OPD area and to reduce the number of critical expires count and LWBS, the initially available six registered nurses from the OPD area were reallocated, (one to the trauma rooms area and one to the ED beds area) making only four nurses available in the OPD area for treatment. Also, out of the initially available four trauma rooms, only two were utilized as there were only two trauma teams available for treatment in that area. Thus, by adding one trauma surgeon and one trauma nurse, an

additional third trauma team was made available for treatment in that area. The simulation was run again for 30 replications, each of six hours. Table 6 summarizes the resource profile of the base model and the model discussed above.

Results and discussion

Increasing resources in the trauma room to three did reduce the critical count to two from the initial count of three, but not to zero. The increase in the number of nurses from 10 to 11 in the ED area did not reduce the LBWS count at all, indicating a need of additional resources at some point in time in both treatment areas. Thus, the above simulation model was rerun for 30 replications, each for a simulation run length of six hours, by reducing the four nurses in the OPD area further to two and moving the two nurses, one in trauma rooms' area and the other in the ED beds area. To make the fourth trauma room available for treatment, an addition of one trauma surgeon and one trauma nurse was made in the trauma room area. Addition of the resources in the trauma rooms area reduced the critical expires count to zero; however, an additional ED bed was required to be added in the standard ED beds area to reduce the LWBS count to zero. The resource profile of the base model and the model that resulted in zero critical expires, LWBS, and zero patients diverted (which, we call the optimal model) for arrival distribution of (1, 2) and simulation run length of six hours is shown in Table 7.

Table 6. Resource profile for experiment 2

ED Treatment Areas	Resources	Initially Available Capacity	Model with Reallocation and Addition of Resources
Trauma room area for severity level 3 patients	Trauma beds Trauma surgeon Trauma nurse Registered nurse	4 2 2 2	4 3 3 3
ED standard beds area for severity level 2 patients	ED beds Emergency physician Registered nurse	15 2 10	15 2 11
OPD area for severity level 1 patients	Registered nurse	6	4

Table 7. Resource profile: base model vs. optimal model

ED Treatment Areas	Resources	Initially Available Capacity	Model with Reallocation and Addition of Resources
Trauma room area for severity level 3 patients	Trauma beds Trauma burgeon Trauma nurse Registered nurse	4 2 2 2	4 4 4 4
ED standard beds area for severity level 2 patients	ED beds Emergency physician Registered nurse	15 2 10	16 2 12
OPD area for severity level 1 patients	Registered nurse	6	2

In a similar fashion, for arrival distribution (1, 2), the number of additional resources required to get zero critical expires, zero LWBS, and zero patients diverted was estimated. The results of additional resources required compared to the initially available resources in each treatment area for distribution (1, 2) for simulation run lengths of 12 hours, 18 hours, and 24 hours were found. Table 8 shows the optimal resource profile for six hours, 12 hours, 18 hours, and 24 hours simulation run lengths.

Table 9 shows simulation results from the base model and the optimal model for six hours. Adding two treatment nurses and one ED bed in the standard ED beds area for treatment of patients with severity 2 reduced "time until first seen" for severity level 2 patients from 5.62 minutes to 5.18 minutes i.e., reducing it by approximately 7%, and thereby getting the LWBS count to zero. The paired t-test found that the difference in means was statistically significant at 0.05 alpha level.

Adding two additional trauma teams to be available for the previously unutilized trauma rooms helped increase the utilization of trauma rooms and also reduced the "time until seen" of patients with severity level 3 from 21.19 minutes to 10.13 minutes i.e., a reduction of approximately 53%, which resulted in a zero critical expires count. The paired t-test for the time until seen for severity 3 patients found that the difference in means was statistically significant at 0.05 alpha level. Reducing nurses in the OPD area from an initial of six to two increased the OPD nurse utilization from 22.52% to 65.65%. The paired t-test found that the difference in means was statistically significant at 0.05 alpha level.

Table 8. Summary of additional resource requirement for different simulation arrival distribution (1, 2) run times

ED Treatment Areas	Base Model		6 hrs	12 hrs	18 hrs	24 hrs
	Resource	No.	No.	No.	No.	No.
Trauma room area for severity 3 patients	Trauma beds	4	4	6	6	6
	Trauma surgeon	2	4	6	6	6
	Trauma nurse	2	4	6	6	6
	Registered nurse	2	4	6	6	6
Std. ED beds area	ED beds	15	16	19	20	20
	Emergency physician	2	2	2	2	2
	Registered nurse	10	12	13	13	13
OPD area	Registered nurse	6	2	2	2	2

Table 9. Simulation results for experiment 2

	Base Model (6 hrs)	Optimal Model (6 hrs)	Percent Change	T-test Results from ARENA Output Analyzer
Time until first seen (severity level 2) in minutes	5.62	5.18	-7.82	Means are significantly different at 0.05 alpha level.
Time until first seen (severity level 3) in minutes	21.19	10.13	-52.19	Means are significantly different at 0.05 alpha level.
OPD nurse utilization (%)	22.53	65.65	191.51	Means are significantly different at 0.05 alpha level.

Thus, the above results show that the capacity of the ED is not only dependent upon the physical resources available but also on the human resources available to treat the patients in a timely manner. Wait times are also affected by the number of available resources and are also dependent upon the arrival distribution. Thus, we can conclude that the capacity of the hospital cannot be estimated alone with the number of available beds, but is also dependent upon the number of human resources available for treatment and the arrival distribution and wait times experienced by the patients.

5.3 Experiment 3

Objective

To study the effect of change in the patient mix on resource utilization and wait times in different treatment areas.

Methodology

The optimal model of arrival distribution (1, 2) for simulation run length of 24 hours was used in this model for studying the objective of this experiment. The model was run for 30 replications with a simulation run length of 24 hours and with percentage distribution of patient types from a confined-space disaster event (See Table 1).

Results and discussion

It was found that, utilization of trauma rooms increased from 29.6% (open-air event) to 92% (confined-space event). Wait times in this area also increased from 9.59 minutes (24 hours optimal model with open-air event patient-injury mix) to 32.21 minutes for confined-space event. Standard ED beds area utilization was reduced to 26% (confined-space injury mix) from 40% (open-air injury mix). Wait times in this area did not change significantly. Thus, knowledge of the type of disaster event that has occurred plays a significant role in planning. Knowing the type of disaster environment would help planners to allocate limited resources in treatment areas where the demand for them would be high. For example, in this experiment, it was found that there will be more demand in the trauma rooms area compared to the standard ED beds area; thus hospitals can plan to convert a few of the ED rooms into improvised trauma rooms, making them available for treatment of critical patients.

6. ADDITIONAL RESULTS

Areas other than the three treatment areas within the ED were also modeled, including x-ray, CT scan, and OR. It was found that CT scan was not a bottleneck when the patient-injury mix was from an open-air event. However, in experiment 3 where the patient-injury mix was changed to confined-space event, it was found to be a bottleneck. X-ray was found to be the most common bottleneck irrespective of disaster event type. Operating rooms were not found to be a bottleneck as there were 14 operating rooms initially available to perform surgery on patients.

Strategies to eliminate radiography as a bottleneck would include bringing in portable x-ray machines to the emergency department and restricting essential services like CT scans for only the most severely injured patients. Another policy that could be adopted to reduce the load on the x-ray machines would be to allow the use of CT scans for patients with moderate injuries when all the victims with severe injuries have stopped arriving. Only when there are no critical patients in the queue waiting for CT scans, can the CT scan be used by the moderate-severity patients.

7. CONCLUSION

Simulation is an excellent tool to model different types of environments. Simulation proves to be a powerful and effective tool for emergency preparedness and disaster planning. Traditionally, planning for a mass casualty event is typically based upon lessons learned from disaster drills or experience from a past disaster. However, not until the disaster strikes is the capability of the plans developed from this exercise realized. Computer simulation allows the disaster response plans to be run under different scenarios and is a useful tool in planning the allocation and utilization of resources. It allows the planner to analyze a wide variety of “what if” scenarios without involving much time and money. It can aid in identifying the overestimation or underestimation of resources identified during physical disaster drills.

This study attempted to show how different types of arrivals, patterns of injury, and time durations for which the disaster victims keep arriving have an impact on the performance of the system. The surge capacity as traditionally defined is the ability of the system to accommodate a huge volume of patients that exceeds the routine daily capacity of the hospital. However, in our work surge capacity is defined in terms of the arrival pattern and the duration for which patients keep arriving at the hospital. The ability of the hospital to accommodate these patients under various arrival patterns over different time durations without compromising the level of care is what we called the maximum capacity of the system.

Various shapes of arrival distributions modeled by using the two parameters (scale and shape) of gamma distribution were tested for different time durations. It was found that the arrival distribution with parameters (3, 4), (3, 3), (4, 2), and (2, 4) did not challenge the institutional capacity. In other words, the hospital was able to treat all the patients without compromising the quality of care up to 24 hours. However, distribution with parameters (3, 2), (2, 2), (3, 1), (1, 2), (2, 3), (2, 1), (1, 4), (1, 3), (1, 1), and (0.5, 2) did affect the system performance. Under these distributions, there was at least one patient who was either dead, LWBS, or diverted. This indicates the immediacy with which victims arriving under these distributions overwhelmed the limited resources.

The model can aid in determining the number of additional resources hospitals would require to treat all victims arriving with the rest of the arrival distribution for different time periods. To conclude, the simulation model built would help emergency planners to better allocate and utilize limited hospital resources in order to treat the maximum patients possible. It also helps estimate the number of additional resources that would be required in a particular scenario.

8. IMPROVEMENTS AND FUTURE WORK

Many improvements can be made in the model. The most important being relieving the assumptions made during the building of the model. Many assumptions made might not be in line with actual protocols and procedures of a given disaster response plan of a particular hospital. The model assigned the priority to treat the victims that were affected by the disaster over the non-disaster-affected patients in each of the treatment areas. However, in a real-life situation, such decisions would be based upon many factors like severity within the patients, age of the patients, and chances of survival. Thus, the model can be further improved by incorporating these real-life situations in assigning treatment priorities to the patients. These improvements would help increase the validity and ability of the model to be used as a decision making tool.

The model currently focuses on ED treatment areas, and CT scan, x-ray, and OR facilities of a hospital. The model can be expanded by including the ICU and inpatient beds in the scope to identify their roles in estimating the capacity of the system. The current model does not take into consideration the number of sub specialist surgeons that would be required in the OR to perform operations on the victims. This can be another possible area of future research. This research can also be extended to model utilization of critical equipment like ventilators. This will involve more detailed simulation modeling but will benefit the hospital management in deploying the resources dynamically. The current model assumes that all facilities within the hospital are fully operational and no damage has occurred to the hospital. There is a possibility that the level of functioning of the hospital could be affected by the attack. If the information on maximum resources that the hospital can add to treat the patients is available, then how to effectively divert the patients to other nearby hospitals when all additional available resources are fully utilized is also a possible direction for future research. The current model does not take into account the effect of over triage on patient wait times and critical mortality. Possible future work could be to study the effect of over triage and under triage on patient wait times, critical mortality and LWBS, and utilization of the resources.

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