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INTEGRATED MODELING OF DISASTER EMERGENCY RESPONSE ACTIVITIES USING SIMULATION: BORNOVA CASE STUDY

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ABSTRACT

We present a detailed integrated simulation model for two processes: casualty transportation and emergency room management after a major disaster. The two important processes have generally been discussed separately in literature. However, to be able to correctly evaluate preparedness of disaster and emergency, and minimize potential loss of lives, it is important that these two interconnected processes are analysed together. The purpose of this study is to present an integrated simulation model of victim transportation and treatment processes after a major disaster and use the proposed model in a case study for Bornova, a district of the city of İzmir in Turkey. Simulation model is run with a detailed experimental design and results are statistically analysed. We find out and report the importance of correct distribution of ambulances to regions and rules for better management of capacities of constrained medical resources in order to minimize total loss of lives.

Keywords: Disaster, Emergency rescue activities management, Discrete event simulation

1. INTRODUCTION

A disaster is a calamitous event that happens with or without a warning, which causes loss of life, injuries and illnesses and damages infrastructure and environment. A disaster can be natural (earthquakes, floods, tsunamis etc.) or man-made (terrorism, technological, fire etc.). For an event to be considered as a disaster, it should either cause significant loss of life, or disrupt normal life. To prevent increased loss of life, it is important to effectively coordinate operations and activities after a disaster (disaster operations). Disaster operations are divided into 4 phases: mitigation, preparedness, response and recovery. This study focuses on operations during the third phase, focusing on response and first aid. This phase includes emergency relief efforts and activities to minimize probability and extent of secondary damage, and to prevent further loss of life. The relevant efforts and activities begin and end within a short span of time due to their nature, before steady-state is reached. This transient period starts from the time victims are rescued and ends when they are treated and released from medical care. To be able to evaluate the effectiveness of, and improve these response activities, it is necessary to investigate the response phase as a whole, rather than in separate parts. This is especially important for a developing country, regularly hit by damaging earthquakes over the last century such as Turkey, and specifically for İzmir, due to its vulnerable location.

Analytical models are mostly inadequate for modeling realistic size complex systems including healthcare systems. The fact that managing disaster operations is a transient period problem, the size and stochastic nature of the problem all make it challenging to model this problem analytically. Even if this kind of problem can be formulated analytically, obtaining a solution for any realistic size may not be possible.

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Flow of patients to the hospitals, scheduling and layout of resources for disaster operations can be realistically modeled using discrete event simulation. For this reason, in this paper, activities in response phase of disaster management, from rescue of the victims to the end of their treatment, are modeled via simulation.

The purpose of this study is to present a detailed simulation model encapsulating both of closely related victim transportation and treatment processes, and to use the simulation model with real-life data in a case study to find out how to manage the constrained resources better and decrease total loss of lives.

Section 2 of this study presents literature review on the subject. The details of the simulation model are presented in section 3. The simulation model is built by using real-life data from İzmir Province Disaster and Emergency Management Center, İzmir Healthcare System Management and the three major hospitals in Bornova, İzmir using ARENA simulation software (version 10.0). Izmir is the third largest city in Turkey and is one of the few metropolitan areas, which has significant earthquake risk. Bornova is one of the most populated central districts of Izmir with a population approaching 450,000. The detailed case study conducted for Bornova can subsequently be scaled up to larger cities. Section 4 includes an extensive experimental design and findings obtained by statistical analysis of the results from the experimental design, performed using the proposed. Finally, section 5 concludes the paper with suggestions on future work.

2. LITERATURE REVIEW

Due to inadequacy of analytical models in modeling complex systems such as healthcare, discrete event system (DES) simulation is used extensively to develop detailed models for problems related to healthcare. Especially for incidents causing mass injuries, which may result in the overloading of healthcare services, DES appears to be an important tool for measuring system response.

To the best of the authors' knowledge, literature found on modeling post disaster response falls into two categories. One group of studies focuses only on transportation of victims to the medical facilities. For instance, Christie and Levary modeled the process of transportation of victims with severe injuries due to a man-made disaster from disaster site to hospitals. The study focused on the issue of how quickly and effectively casualties should be transported in order to provide timely medical treatment and reduce the loss of life [1]. Fawcett and Oliveira suggested a new approach to the problem of providing medical assistance to victims after a major earthquake. Based on a mathematical model, they tried to determine how regional medical systems should respond to earthquake. The inputs of the model are the location and number of non-fatal casualties, the level of pre-hospital medical care, and the capacity of hospitals and transportation system post-earthquake. The simulation model simulates the flow of the victims from the areas affected by the event to the hospitals. Since some or all of the hospitals in the disaster region may be damaged, hospital care capacity is also included in the modeling process. In the model, there is no difference among types of casualties; all victims in need of hospital care are taken into account. The proposed model also estimates the statistics related to the system response such as the number of loss of life, the waiting time before treatment etc [2]. Sullivan states that computer simulation can test planning ability under different scenarios and can help planners in decision process. For this reason, at the stage of emergency service systems planning for the events with mass death and injuries, the author suggests that DES should be used as a part of the planning process. In the study, various decision rules related to the time of calling outside ambulances are evaluated. It is stated that the simulation model accurately models the response to Greensburg tornado occurred in the year of 2008 [3]. Ullrich, Debacker and Dhondt developed a simulation model focusing on the prehospital phase consisting of field triage, evacuation and medical processes. With the model, they studied the effects of several parameters, such as the number of hospitals, medical teams and ambulances on several performance indicators [4].

The other group of studies focuses on patient flow in emergency department. Au-Yeung, Harrison and Knottenbelt modeled the patient flow in the emergency department of a large hospital using a Markov queuing network model, which includes multiple casualty types. To determine the parameters of the model, real data were used. Probability density functions and moments related to the patient response time were obtained by means of DES. Furthermore, the results were compared using different prioritization rules according to the casualty types [5]. Based on the assumption that the predictions of hospital capacity will support emergency rescue activities, Paul et al. state that it is important to accurately model the system behavior immediately after the event causing a disaster. With this aim, they suggest a transient modeling approach which uses simulation and exponential functions. In addition, the idea that arriving time from the event region to hospital can affect victim's health status is reflected to modeling process [6]. Patvivatsiri generated a simulation model to analyze the patient flow in an emergency department, evaluated the usage of emergency department resources and determined appropriate resource and personnel levels [7]. Joshi modeled the effect of different arrival processes of patients to hospitals using DES. The study consisted of an analysis of patient flow to an emergency department after terrorist attack. They aimed to determine how emergency department patient care sufficiency is affected according to different arrival processes [8]. Yi et.al. developed a simulation model to represent hospital operations in the disaster situation after an earthquake, and obtained generalized regression equations to determine steady-state hospital capacity using the results from the simulations. Following this, a parametric metamodel was used to estimate transient capacity for multiple hospitals [9]. Based on earthquake data, Cao and Huang developed a simulation model to determine the performance of different prioritizing strategies for victims in need of medical treatment under varying resource levels [10]. Wang, Jiang and Yu developed two models to simulate casualty arrivals in, and medical treatment capacity of a hospital for a biochemical terrorist attack scenario. Changing the number of servers, they aimed to determine the number of victims treated within an hour, named the golden hour [11].

To the best of the authors' knowledge, current literature on the subject concentrates on either casualty transportation or on emergency room management. However, these processes have input-output relationships; a change in settings of one process is highly likely to have effects in the downstream processes. Because the proposed model incorporates real life data on all processes, it is possible to realistically estimate effects of any setting or scenario on saving lives.

3. SCOPE AND MODEL

Worldwide, between 2002 and 2011, an average of 107,000 died annually because of natural disasters. During this interval, earthquakes were the leading cause of deaths with an average of 67,974 deaths annually [12]. Due its global position, Turkey is especially prone to earthquakes. Major metropolitan areas, with dense population, are under earthquake threat. Specifically for İzmir, the third largest metropolitan area of Turkey, with a population of 4.5 million, earthquake is listed as number one cause of life loss and property damage among disasters, according to official Emergency Aid Plan [13]. Bornova is chosen for the case study since it is one of the most populated central districts of Izmir with a population approaching 450,000. The results and findings from a detailed case study for Bornova are appropriate for scaling up.

For these reasons, the proposed model is developed mostly for earthquake scenarios, based on assumptions from previous earthquake related studies, making the model and its output realistic. The model includes first medical aid, triage, victim classification into priority classes, and transportation to hospital using ambulances and treatment in emergency rooms. The actual rescue of victims is excluded. To ensure that the proposed simulation model accurately represents real life system, the details of listed individual processes are modeled based either on manuals, emergency plans, or on expert interviews. In addition, static data used are either real life data or taken from previous similar subject studies in literature, as listed. To ensure that the model is built correctly as regards to the conceptual model, animation is utilized. Smaller test problems are run first to ensure that the proposed simulation model is in line with the conceptual model.

We first present the general settings and assumptions for the proposed model developed in ARENA simulation software below. The flow of the simulation model is provided in Figure 1. (The specific setting and any additional assumptions made for Bornova case study will be presented later.)

Simulation Model Settings

1. Victims are defined as people who are injured in an earthquake and are in need of medical help. The victims are placed in one of three (3) priority classes. Priority class 1 victims are seriously injured and face imminent loss of life if not treated. Priority class 2 victims are those who can wait for treatment but have to be admitted to a hospital for recovery. Finally, priority class 3 victims can be treated without being admitted to a hospital.

2. Each victim generated will be assigned a number of attributes. These attributes include region where the victim is from (the area affected by disaster is divided into regions), the severity of sustained injury (therefore priority class), expected remaining lifetime if untreated, etc.

3. After a location for triage is secured, it becomes a casualty collection point (CCP), which a field first-aid unit is settled. The field first-aid unit is responsible for classifying victims into priority classes and providing initial (basic) treatment.

Simulation Model Assumptions

1. It is assumed that, after an earthquake, the available standing medical facilities are known. The model can easily be used for varying assumptions of available (standing) facilities.

2. The process of rescuing victims is excluded from the simulation model. Modeling actual rescue efforts requires extensive information and expertise on earthquakes, building structures and damage created, and changes significantly based on location and actual building inventory. Also after a disaster, e.g., a major earthquake, a large proportion of uninjured survivors participate in search and rescue efforts alongside professional teams and efforts. For these reasons, rescue efforts are not relevant to the scope of this paper, which is limited to modeling response activities in regard to victims. The purpose of this research is to concentrate on the transportation and treatment of victims after a major disaster. Modeling rescue efforts in a post-disaster environment will therefore not contribute to the usefulness of results for this study.

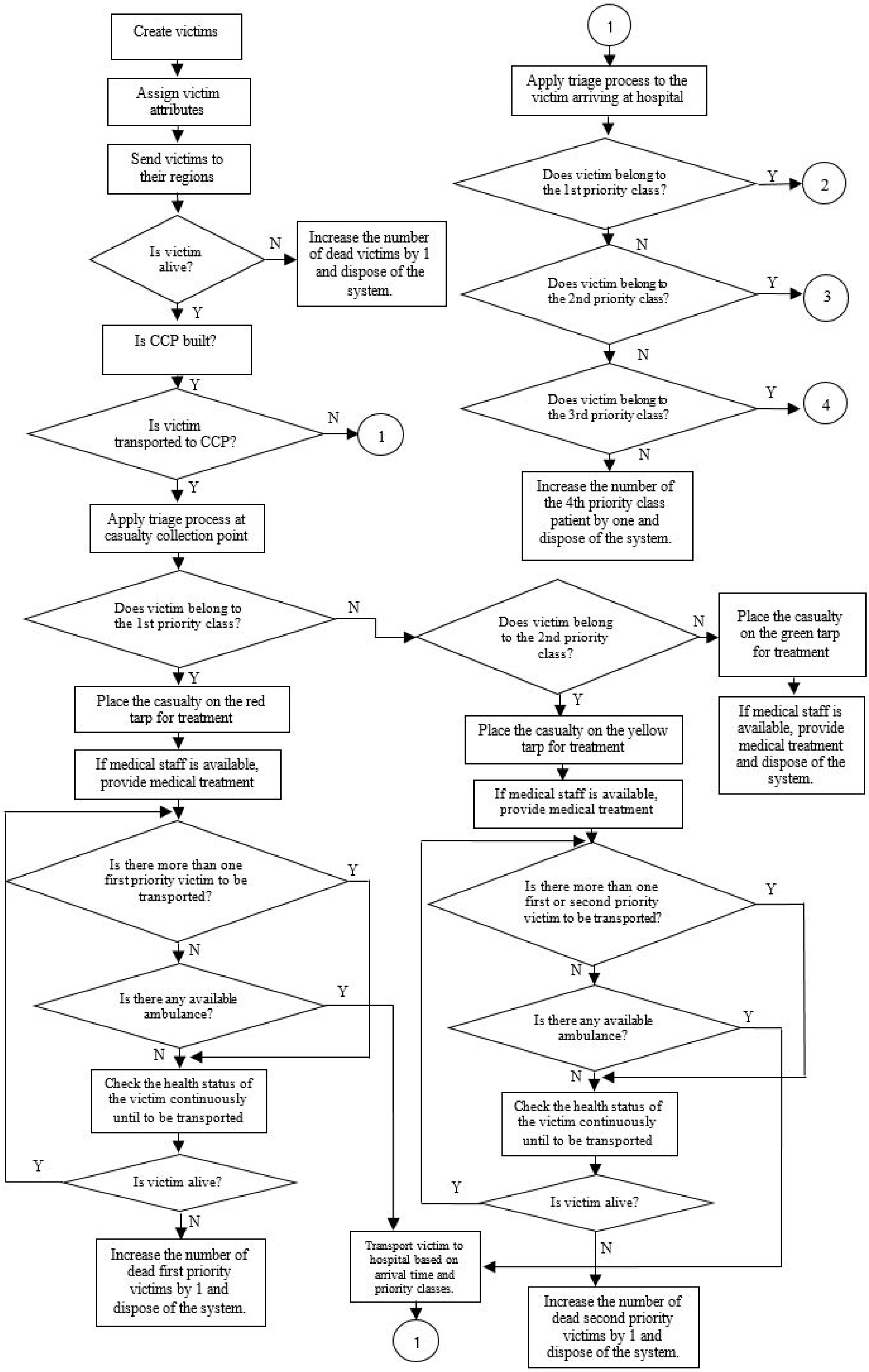

Figure 1. Flow chart of the simulation model

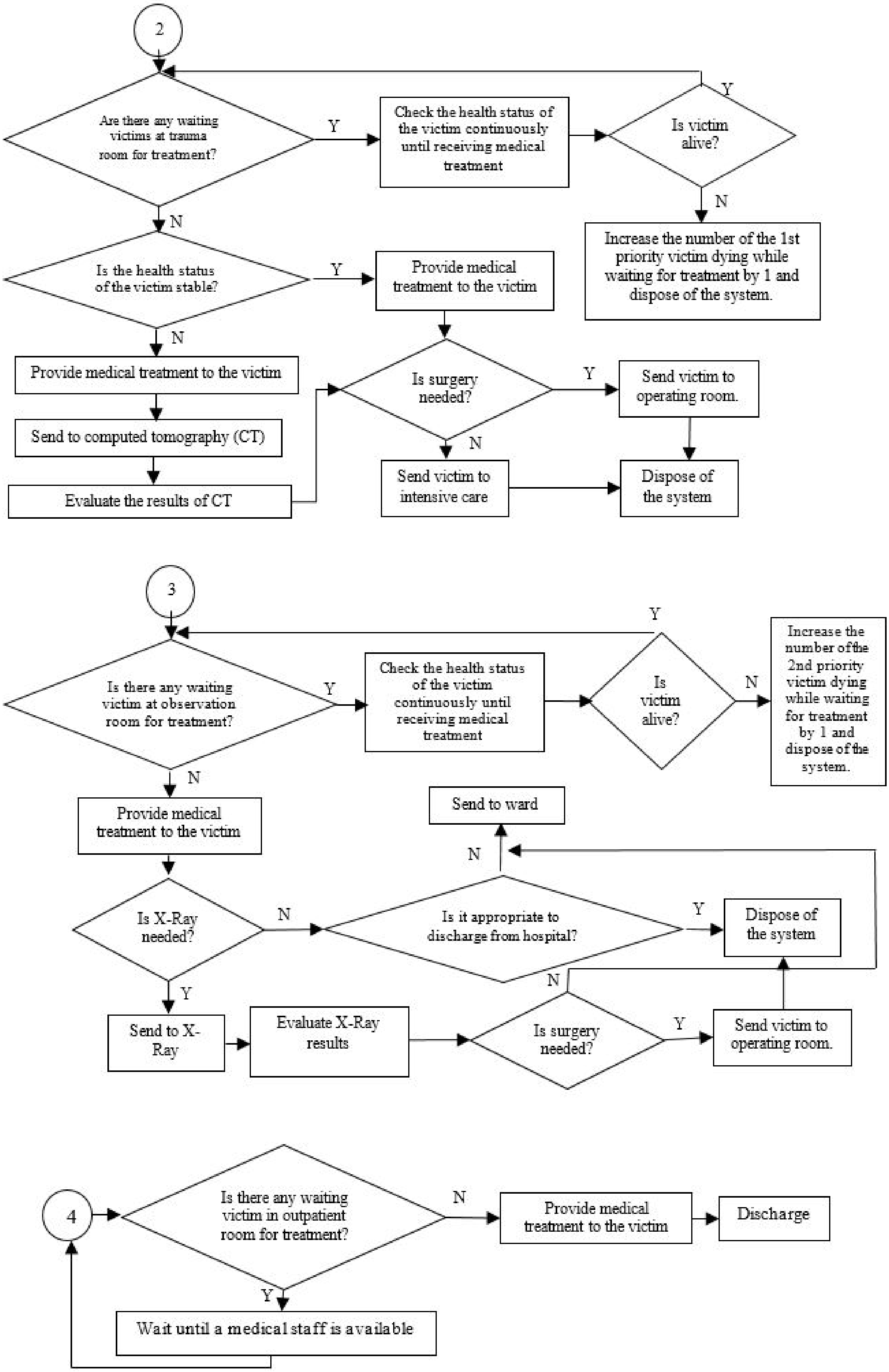

Figure 1. (Continued) Flow chart of the simulation model

3. Interarrival times of victims are assumed to be exponentially distributed. The interarrival time can be adjusted to cover a wide range of distributions. Nevertheless, exponential distribution is a good assumption when little information is available. Once the victims arrive into the model, they are assigned one of the three priority classes. The arrival rate is time heterogeneous and is determined based on previous studies using past earthquake data [14-16]. It is therefore assumed that 20% of victims are rescued within the first 30 minutes, 40% within the first 3 hours, and 47.5% within the first 8 hours. The fraction reaches to 55% within the first 12 hours, 70% within the first 24 hours and 85% within the first 48 hours. The interarrival times of victims are calculated using population numbers and rescue fractions mentioned above.

4. The casualty collection points are assumed to be operating at the predetermined tent-city locations [17].

5. The model assumes that the first medical teams arriving after the earthquake set up at the casualty collection points and form field first-aid units. Depending on the existence of field first-aid units, victims are either directed to CCP or to medical facilities. Casualties are sent either to field first-aid units, if established in the region, or to hospitals according to user defined preset fractions. According to Mirhashemi et al., due to sun-dried construction of 80% of houses, majority of the buildings were destroyed during Bam earthquake and it took the first rescuers 1.7 hours on average to reach the scene [18]. Considering its stronger and the existence of a well-rehearsed emergency aid action plan, we can assume for Izmir, the time to reach incident site would be shorter. The model assumes a 45 minutes delay for the first responders to setup casualty collection and triage areas, start treatment of patients, and direct them to hospitals.

6. Rescued victims are transported to the hospitals using ambulances at a CCP or by other means if at other locations. Fractions of victims using each mode of transportation are user set, and can be used at different values for the experimental design. Victims categorized into priority class 3 are assumed not to require ambulances.

7. The simulation model assumes that the area affected is divided into regions. These regions can be towns, neighborhoods, municipalities etc. As per common real-life practice, the closest ambulance available to the region is sent, when required.

8. The transportation of patients from either the wreckage sites or triage areas is performed according to priority classes. A first priority class victim will have access to an ambulance before the second. Each ambulance will leave as soon as it receives a 1st priority class victim; but can accommodate two victims.

9. The time for a triage is assumed to be 1 minute [19]. Upon arrival to the hospital, treatment of victims is conducted according to the priority classes assigned during triage.

10. 65% of priority 2 victims arriving at the hospitals require X-ray machine.

11. The third priority class patients are treated by nurses and treatment time is assumed to be distributed according to U~ (5, 20 min.). After treatment, patients leave the system as healed. Other treatment time distributions used in the simulation model along with references are given in Table 1.

Table 1. Treatment time distributions used in the simulation model

	1st priority casualty	2nd priority casualty	Reference *
Max. waiting time without treatment (min.)	TRIA(45,80,150)	TRIA(180,360,480)	[6]
Time for first aid administered on rescue site (min.)	TRIA(10,20,30)	TRIA(5,10,15)	[21]-[22]
First treatment time in trauma room for unstable patients (min.)	TRIA(5,20,50)	-	[20]
First treatment time in trauma room for stable patients (min.)	TRIA(15,45,90)	-	[20]
CT Scan time (min.)	TRIA(10,30,55)	-	[23]
Treatment time of patients in observation room (min.)	-	TRIA(20,40,75)	[20]
X-ray time(min.)	-	TRIA(10,20,40)	[20]

* Distributions given in Table 1 are based on referred publications. In cases where more than one reference provided or where the referred publication does not provide exact details of the distributions, information is combined from multiple sources and/or necessary extrapolations based on provided data are made.

Bornova Case Settings

1. According to Emergency Aid Plan created by İzmir Governorship, tent-cities are to be constructed in the following four locations: The vicinity of Bornova Teacher's House, Bornova Anatolian High School, Bornova Youth and Sports Park, and Trailer Park in the 4th Industrial Site. These locations are marked on the Figure 2.

Bornova Case Assumptions

1. Total number of victims in the simulation model is created based on official estimates of İzmir Emergency Aid Plan and the population of Bornova, İzmir. İzmir Emergency Aid Plan estimates the total number of victims in the range from 0.5% to 1.5% of population. Using 1.0% as a medium level, experiments are constructed for 0.5%, 1.0% and 1.5% of population for the total number of victims in Bornova. These values, together with time-heterogeneous rescue rate of victims, are used to generate victim interarrival times.

2. The thirty three (33) neighborhoods of Bornova are grouped into 5 regions, based on İzmir Emergency Aid Plan and their proximity to each other.

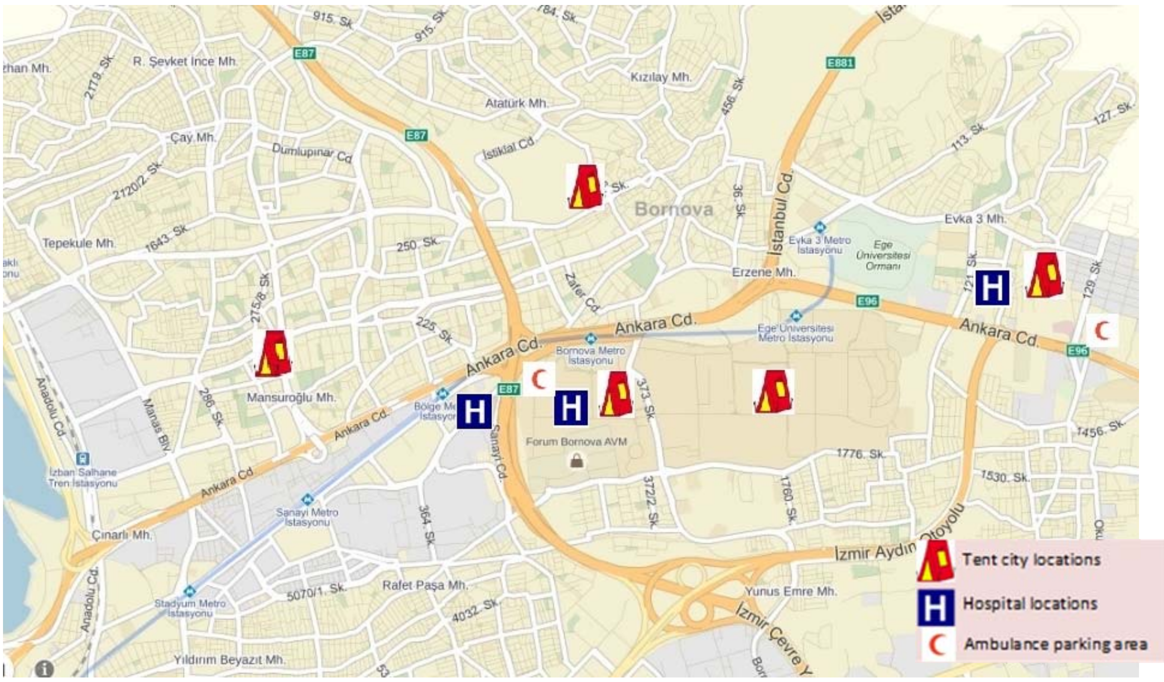

Figure 2. Bornova map

3. As of the study date, based on official numbers from İzmir Healthcare System Administration, there are a total of 278 ambulances in İzmir, 73 of which are for emergency use and the rest, for patient transportation. In proportion to its population, Bornova is assumed to have 12 emergency and 34 patient transportation ambulances available.

4. There are two (2) ambulance-waiting locations in Bornova, one near each major hospital, as presented in Figure 2. In accordance with the population of the regions, it is assumed that 31 ambulances will be available at location 1 near Hospital 1, and 15 at location 2, near hospital 2.

4. EXPERIMENTAL DESIGN AND ANALYSIS

The proposed simulation model for Bornova is used to analyze ambulance waiting times and trauma and observation room waiting times of recovered patients, in subsections 4.1, 4.2 and 4.3, respectively. Assuming a significance level of α=0.05, 30 replications were found to be sufficient for the experiments. Results are analyzed using statistical package SPSS (version 15.0). These analyses and their results are given in subsections 4.1, 4.2, and 4.3 respectively.

4.1. Regression Analysis of Mean Waiting Time for Ambulance

The variables used in experimental design effecting ambulance waiting times and their different levels are listed in the Table 2 given below.

Table 2. Experimental design factors for ambulance waiting times

Variables	Levels
Number of ambulances (x_1)	46(31-15)-51(34-17)-59(39-20)
Fraction of the people who know the existence of casualty collection points (x_2)	0.10-0.30-0.50-0.70
Fraction of the people who want to go to the casualty collection points in the site (x_3)	0.20-0.40-0.60-0.80
Fraction of the priority 1 casualties (x_4)	0.10-0.15-0.25
Fraction of the priority 2 casualties (x_5)	0.25-0.35
Fraction of the total of casualties (x_6)	0.005-0.010-0.015

In order to determine mean ambulance waiting times of each region, dummy variables are used as defined below:

$$d_i = \begin{cases} 1, & \text{if region } i \\ 0, & \text{otherwise} \end{cases} \qquad i = 2, 3, 4, 5$$

If a particular d_i is 1, the resulting estimate from the regression will give expected ambulance waiting time in region i. If $d_i = 0$ for i = 2, 3, 4, 5, regression gives expected ambulance waiting time for region 1. The resulting regression model is given below:

$$\begin{aligned} \ln \hat{y} = {} & 2.372 - 0.016x_1 + 0.516x_2 + 0.368x_3 + 1.357x_4 + 2.112\,x_5 + 84.108x_6 \\ & -0.179d_2 - 0.654d_3 - 0.349d_4 - 0.757d_5 \end{aligned}$$

In order to determine whether the assumptions of regression analysis are satisfied and the model is valid, first, the existence of multi-collinearity is examined. In order to comment on multi-collinearity problem, it is necessary to examine tolerance or variance inflation factor (VIF) values obtained via SPSS output (Table 3). Tolerance is an indication of how much of the variation in an independent variable is explained by the other independent variables. If the value of tolerance is less than 0.1, the multiple correlation related to the other independent variables is high, indicating the existence of multi-collinearity. VIF is the inverse of tolerance value. A calculated VIF value greater than 10 is considered a possible indicator of multi-collinearity. According to the SPSS output, it is seen that these values do not exceed the reference values; therefore multi-collinearity can be considered not to exist. In order to comment on outliers, Mahalanobis distances can be used. In the output, minimum and maximum values of Mahalanobis distances are given. For 10 independent variables, the critical value is 29.59. In the results obtained at the end of regression analysis, it is seen that the maximum value of Mahalanobis distances is 13.408, which does not exceed the critical value. The situation that Cook's distance is not greater than 1 indicates no important problem in the data. In order to test the assumption that errors in regression are independent, Durbin-Watson test statistic is used. If calculated value of the statistic is close to 2, then this assumption is almost certainly satisfied. For these data, the value of the statistic is 2.080, therefore the assumption of independent errors is considered to be satisfied. To check whether the assumptions of homoscedasticity and linearity are met, a plot of standardized residuals against standardized predicted values shows that the data points are randomly dispersed around zero, indicating that these assumptions are satisfied. In addition, to test the normality of residuals, histogram and normal probability plot are drawn. The histogram of residuals shows a bell-shaped curve and points in the normal probability plot of residuals form a straight line, showing no evidence of significant deviation from the normality. The result of Kolmogorov-Smirnov test on standardized residuals (Kolmogorov-Smirnov Z= 1.169, p= 0.130) also supports this conclusion.

Table 3. SPSS output related to regression coefficients and collinearity statistics

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	2,372	,020		116,703	,000		
x1	-,016	,000	-,174	-67,314	,000	1,000	1,000
x2	,516	,006	,230	88,973	,000	1,000	1,000
x3	,368	,006	,164	63,401	,000	1,000	1,000
x4	1,357	,033	,147	41,355	,000	,526	1,900
x5	2,112	,036	,211	59,082	,000	,526	1,900
x6	84,108	,318	,685	264,758	,000	1,000	1,000
d2	-,179	,004	-,143	-43,613	,000	,625	1,600
d3	-,654	,004	-,521	-159,354	,000	,625	1,600
d4	-,349	,004	-,278	-84,993	,000	,625	1,600
d5	-,757	,004	-,604	-184,594	,000	,625	1,600

a. Dependent Variable: ln_y

The regression model and all of the coefficients in the model are statistically significant (p=0.000[1] < 0.05). According to the regression model, it can be said that the fraction of total of casualties is the factor with the greatest effect on ambulance waiting times. The number of the ambulances does not have significant effect on waiting times. The number of ambulances decreases waiting times, but due to the overwhelming number of casualties relative to the available ambulances, an additional ambulance has no significant effect on ambulance waiting time.

Figure 3 presents ambulance waiting times for 5 regions at different levels of total casualty fraction and priority 1 victim fraction (source data for Figure 3 is provided in Appendix). Each row shows

[1] SPSS analyses are done with 4 significant digits. For this reason, p=0.0000 should be evaluated as almost zero.

expected ambulance waiting times for varying *number of ambulances* and *total casualty fractions*, when *fraction of the people who know the existence of casualty collection points* (x_2)*=0.1, fraction of the people who want to go to the casualty collection points in the site* (x_3)*=0.2, fraction of the priority 2 casualties* (x_5)*=0.25*. The first priority casualty fraction is low for column 1 (*fraction of the priority 1 casualties* (x_4)*=0.1*) and high for column 2 ((x_4)*=0.25*).

From the data, one can calculate that each 0.5% increase in total casualty fraction is expected to increase ambulance waiting time by approximately 52.27%. Expected ambulance waiting times are seen to be longest for casualties in region 1 and shortest for region 5. It can also be calculated that about 13 extra ambulances are needed to provide the same ambulance waiting time when the first priority casualty fraction increases 15% (from low level to high level), meaning that for each 5% increase in the first priority casualties, a corresponding increase in ambulance waiting time can be offset by the addition of approximately 4.24 ambulances. A similar analysis for second priority casualties reveals that 13 extra ambulances can cover only a 10% increase in the second priority casualties.

Regions 1 and 2 have significantly longer expected average ambulance waiting times compared to regions 3 and 5. In addition, the effect of number of ambulances to expected average ambulance waiting times (slope) is significantly larger for regions 1 and 2 compared to regions 3 and 5. Therefore, any additional ambulance would have greater immediate impact in regions 1 and 2, compared to other regions.

From Figure 3, we can also understand that the effect of the first priority casualty fraction on ambulance waiting times is significantly greater in regions 1 and 2, compared to other regions. Therefore, any effort to decrease the first priority casualty fraction would have greater immediate impact on ambulance waiting times in regions 1 and 2.

There is an apparent imbalance of ambulance waiting times between regions. When the number of ambulances is limited, the regression model can be used to find optimum distribution of the ambulances among the regions. Chaotic conditions can occur after a disaster. However, this regression model obtained as a result of extensive simulation experiments can be used to estimate the effect of any particular distribution of ambulances across the regions, by calculating the expected average ambulance waiting times. For this reason, the model will be one of the most important inputs for an ambulance-distribution optimization study.

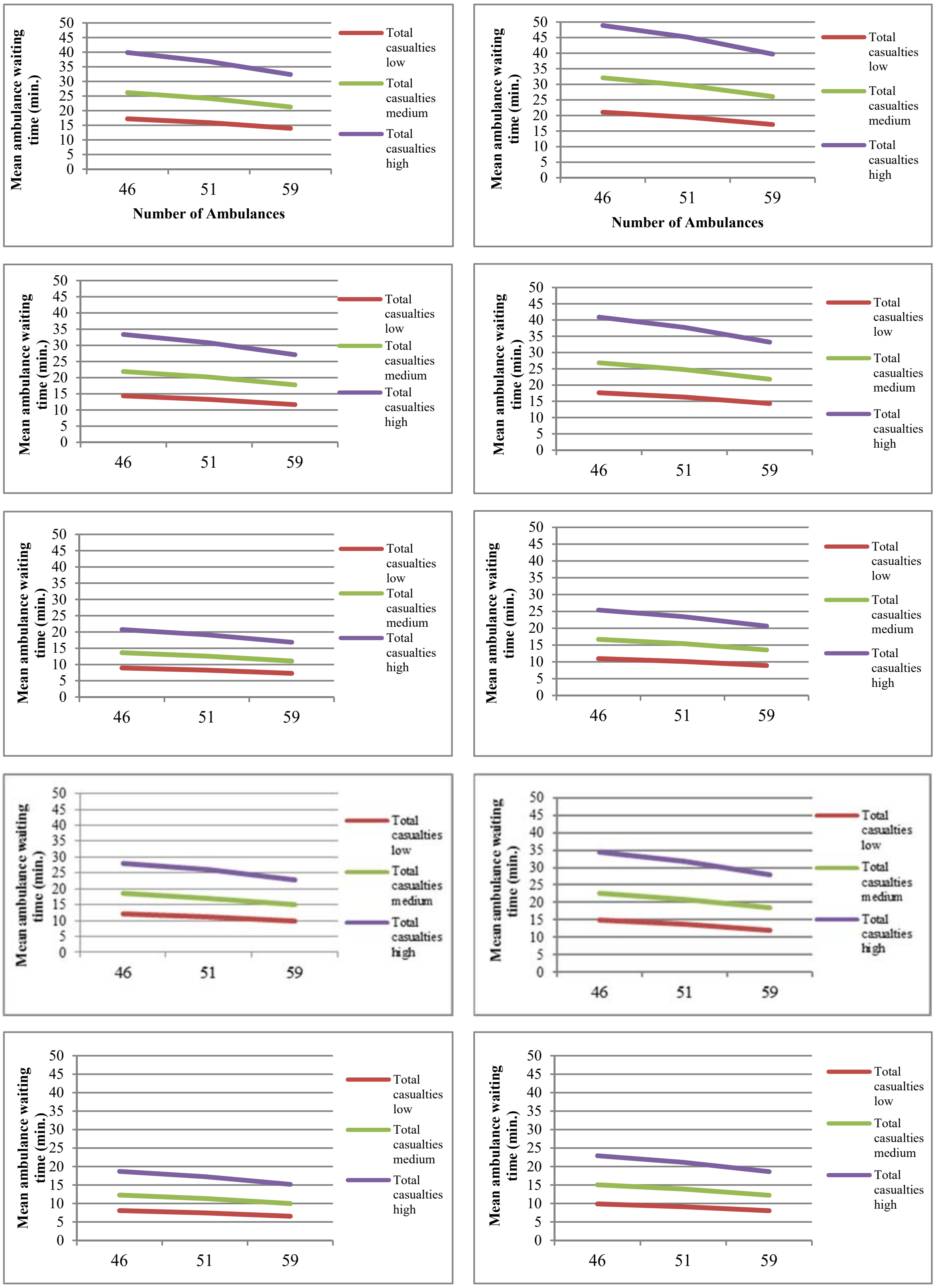

Figure 3. Ambulance waiting times for 5 regions for varying total casualty fractions (0.5%, 1% and 1.5%) at low level of priority 1 casualties (column 1) and high level of priority 1 casualties (column 2)

4.2 Mean Waiting Time for Treatment in Trauma Rooms

In this section, trauma room waiting times are analyzed. It is important to know which factors affect waiting times at trauma rooms, so that before a disaster strikes, resources can be more effectively distributed in order to decrease waiting times, and reduce resulting loss of lives. Table 4 shows factors and the levels used in the experiments implemented in order to determine how various factors are effective on the waiting times for treatment of priority 1 casualties.

Table 4. Experimental design factors for mean treatment waiting time in trauma rooms

Variables		Levels
Number of beds in trauma rooms	Hospital 1	7-12-20
	Hospital 2	2-4-8
	Hospital 3	3-6-12
Number of triage personnel in hospital		1-3-5
Priority 1 casualty fraction in the population		0.15-0.25
Unstable casualty fraction		0.15-0.20-0.25-0.35
Total casualty fraction		0.005-0.010-0.015

Results of analysis of variance (ANOVA) for each hospital are similar. For this reason, only results of ANOVA for hospital 1 are presented here. Assumptions of ANOVA are also tested. Normality assumption of error terms is tested in two ways, using the histogram of residuals, and also Kolmogorov-Smirnov test (Kolmogorov-Smirnov Z= 1.259, p= 0.084). The plot of residuals against fitted values shows that the linearity assumption is satisfied. According to the results of analysis of variance, it is seen that main effects of all factors are statistically significant at the 0.05 level. In addition to this, the interactions between the number of triage personnel and the number of beds, total casualty fraction and priority 1 casualty fraction are also statistically significant at the 0.05 level. The F-value computed for the number of triage personnel (F=12119.41; p=0.000) is higher compared to the other factors, showing that this factor is highly influential on mean waiting time. This is due to the increased number of patients treated in the trauma room per unit time increases as the number of triage personnel increases. Other factors that have important effect are total casualty fraction (F=1057.07; p=0.000), priority 1 casualty fraction (F=719.40; p=0.000) and the interaction between the number of triage personnel and total casualty fraction (F=377.18; p=0.000). These two factors also contribute to higher number of casualties, and hence increase total number of victims for trauma room.

When variance homogeneity cannot be satisfied, as in this case (Levene's test result of equality of error variances: F=8.660, p=0.000), Games-Howell test can be used to determine if there is statistically significant difference between the levels of any one given factor. Games-Howell multi-comparison test is applied to all factors for trauma room waiting time. We present the results on the mean waiting time for treatment in the trauma room which belong to the factors having statistically significant differences between their levels are interpreted as follows:

i) *The number of triage personnel*: According to the test results, as the number of triage personnel increases, it is observed that mean waiting times for treatment also increase (Figure 4) and this increase is statistically significant (for all levels, p=0.000). From the simulation results, long queues are observed (in front of triage process) although the duration of triage operation is short. The longer the waiting time for treatment, the higher the number of fatalities in the queue; therefore, the response of system for the available capacity is evaluated at different triage staff levels. Based on the results, it is recommended that, for each treatment entry point, there should be one member of triage staff or a two member triage team. In this situation, different levels of triage staff would require alternative treatment areas with capacity to conduct emergency service operations, to be constructed in or around hospital. In other words, changes in the levels of triage and trauma room capacity should be closely linked and changed (increased or decreased) together. The relationship between increase in trauma room waiting time with increased triage staff level can be explained by the notion of the shifting bottleneck. Increase in triage staff level allows more victims into the trauma room for treatment per unit time, effectively making the trauma room the new bottleneck. In Figures 4-5, the averages calculated over all the results of the simulation for values of the factor in horizontal axis, are shown by black straight line. In real life, it is quite probable that theoretical distributions will not be (partially) linear. The red dashed lines in Figures 4-5, illustrate the authors' theoretical distribution predictions (convex/concave) based on the obtained results. In this manner, Figure 4 shows the effect of triage personnel on treatment waiting time in trauma rooms.

ii) *Total casualty fraction:* According to the result of the multiple comparison test, as the casualty fraction increases, it is observed that waiting time decreases (Figure 5). This decrease is statistically significant for only the 1st and 3rd levels of the factor (p=0.000). It seems counterintuitive that mean waiting time increases with increased total casualty fraction. Remember that total casualty fraction was also the factor that most affected ambulance waiting time in section 4.1. With increased number of casualties, victims spend more of their remaining life time waiting for ambulances. As the number of casualties increases, it is seen that the number of losses in the treatment queue at the third level of the factor (0.015) is three times greater compared to the first level (0.005). This shows that many are lost before receiving treatment, therefore reducing mean waiting time for those who survive long enough to get treatment.

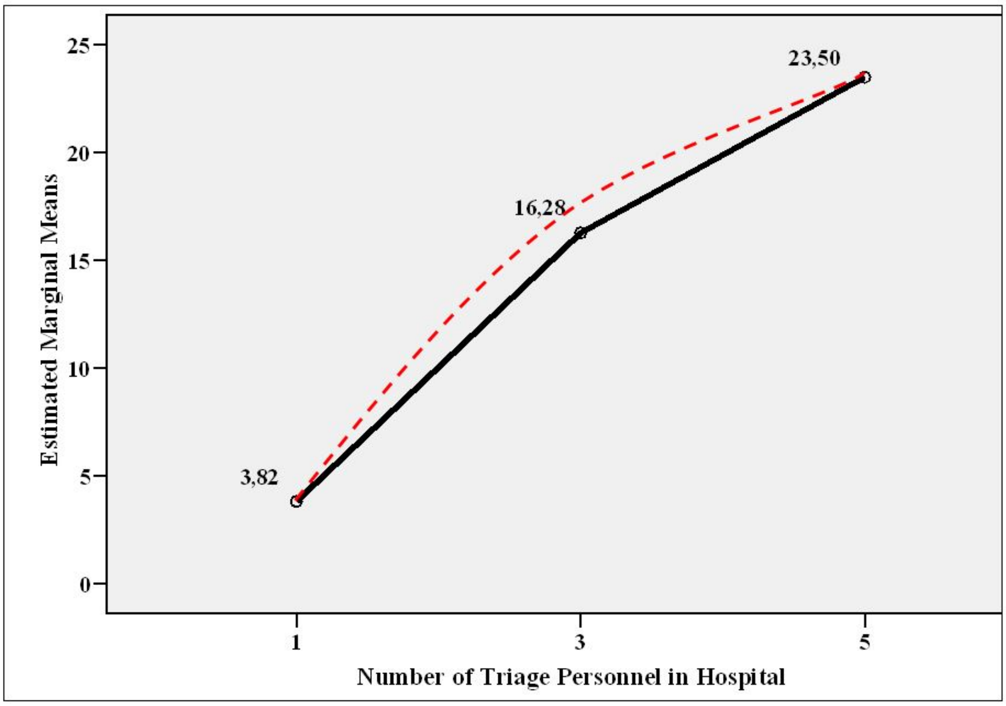

Figure 4. Effect of the number of triage personnel on mean waiting time for treatment (min.) in trauma room

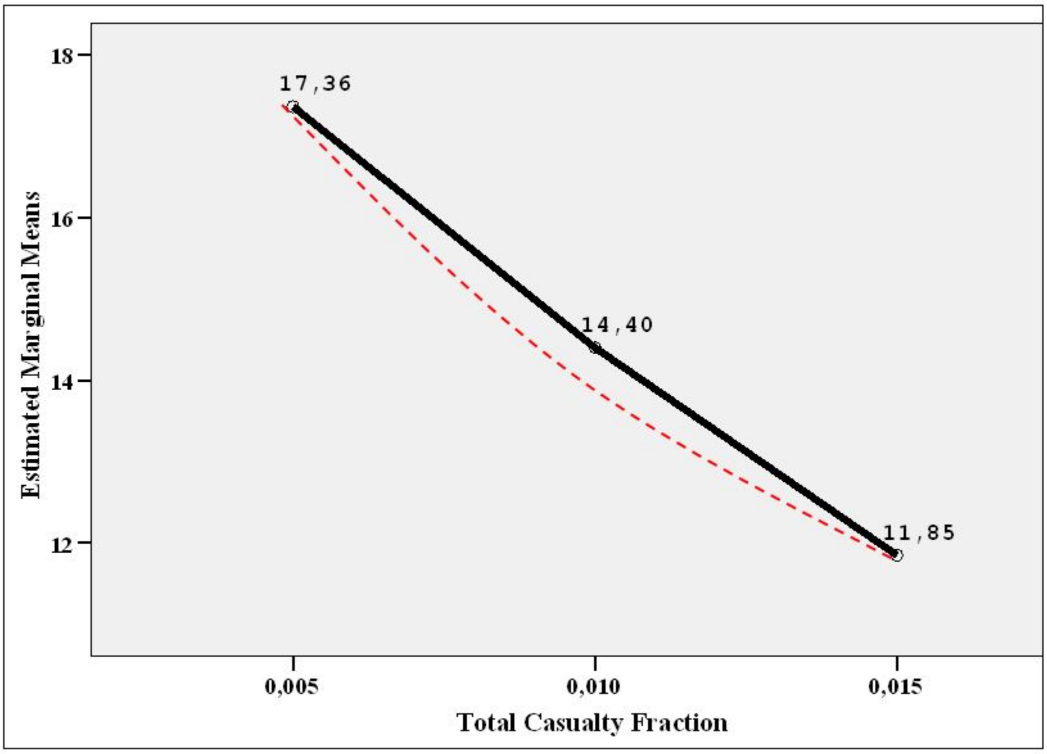

Figure 5. Effect of victim fraction on mean waiting time for treatment (min.) in trauma room

4.3 Mean Waiting Time for Treatment in Observation Rooms

Lastly, we present an analysis determining the effects of various factors on mean waiting times at observation rooms. The second (2nd) class priority victims are forwarded to observation rooms. Table 5 shows the factors and the levels used in the experiments implemented in order to determine effectiveness of various factors on the waiting times for treatment of priority 2 casualties.

Table 5. Experimental design factors for mean treatment waiting time in observation rooms

Variables		Levels
Number of beds in observation rooms	Hospital 1	15-25-35
	Hospital 2	4-8-15
	Hospital 3	4-8-15
Number of triage personnel in hospital		1-3-5
Priority 2 casualty fraction in the population		0.25-0.35
Total casualty fraction		0.005-0.010-0.015

Analysis of variance (ANOVA) is performed based on the results of the experimentation. As in section 4.2, the results of ANOVA are similar for each hospital, and therefore results for only hospital 1 are discussed here. Again, normality assumption of error terms is tested by both analyzing the histogram of residuals, and conducting Kolmogorov-Smirnov test (Kolmogorov-Smirnov Z= 0.922, p= 0.363). The plot of residuals against fitted values shows that the linearity assumption is satisfied. According to the results of ANOVA, main effects of all factors, except number of beds, are statistically significant. However, similar to the previous analysis results, interactions between priority 2 casualty fraction, total casualty fraction and the number of triage personnel are also statistically significant. We also observe that the factor with the greatest impact on the average waiting time in the observation room is the number of triage staff (F=9451.33, p=0.000). The second greatest effect was the interaction of this factor with total casualty fraction (F=1741.54, p=0.000). For the reason explained in section 4.2, increasing levels of mentioned factors will increase the number of victims reaching the observation room in the given time interval, resulting in increased waiting times in the observation room.

When variance homogeneity can be satisfied, as in this case, (Levene's test result of equality of error variances: F=1.278, p=0.125), Tukey HSD test can be used to determine if there is statistically significant difference between the levels of any one given factor. Tukey HSD multi-comparison test is applied to all factors relating to observation room waiting time. According to Tukey HSD multiple comparison test, the effects on the average waiting time for treatment in the observation room which belong to the factors having statistically significant differences between their levels are as follows:

i) Number of triage personnel**:** When the number of triage staff at the entry of emergency room is increased from 1 to 3, an average of 19-minute increase in the waiting time is observed. Similarly, when the number of triage staff is increased from 3 to 5, an increase in the waiting time of approximately 1 minute is observed (Figure 6). According to the test results obtained, it can be said that differences for all levels are statistically significant (p=0.000). The mean waiting time in observation rooms is higher when compared to trauma rooms. This is due to priority 2 casualty fraction being larger than priority 1 fraction, and priority 2 patients' ability to survive for longer without treatment.

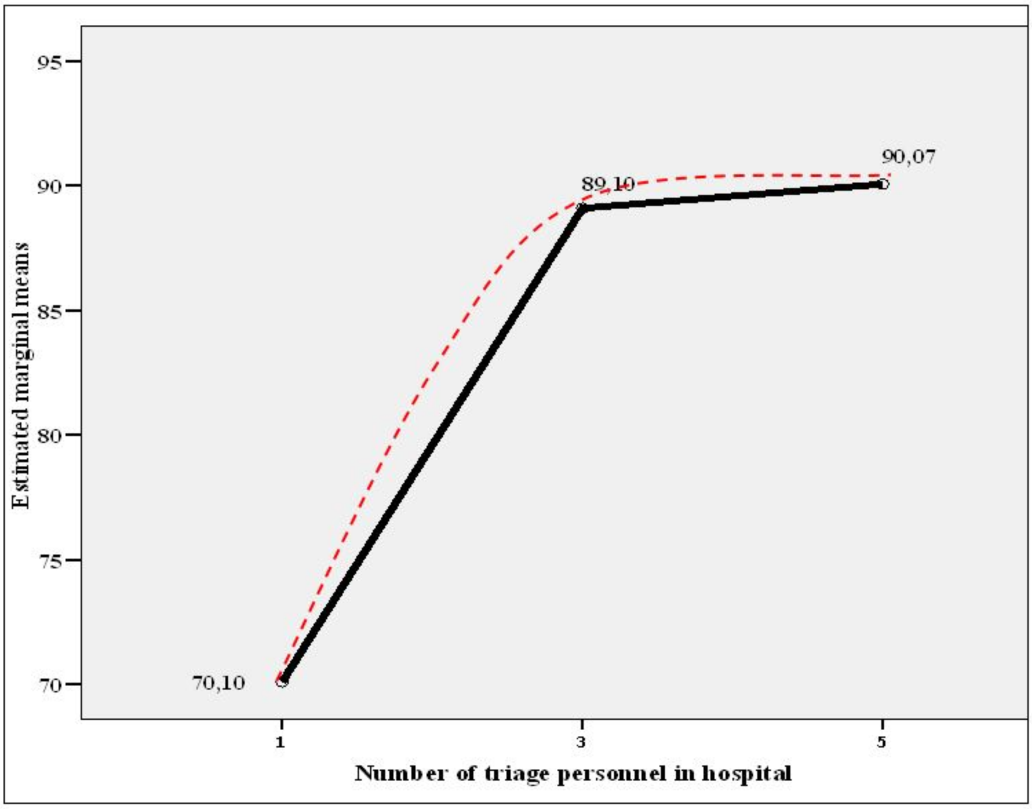

Figure 6. Effect of the number of triage personnel on mean waiting time for treatment in observation room

ii) Total casualty fraction: According to the simulation results, when total casualty fraction is increased from level 1 to the level 3 (a three-fold increase); 5.5 times increase in loss of life is observed. This situation explains the reduction in mean waiting time for treatment of increasing total casualty fraction. While this decrease is not statistically significant for levels 1 and 2, it is significant for levels 1-3 and levels 2-3 (*p*=0.000 for those who are significant). Increasing total casualty fraction from level 2 to level 3 causes an approximately 7-minute decrease in the mean waiting time. Therefore, in terms of waiting time in the observation room, there is a critical value for total casualty fraction between 0.01 and 0.015. The exact identification of this value requires a more detailed simulation study, with more steps between the 0.01 and 0.015 (Figure 7).

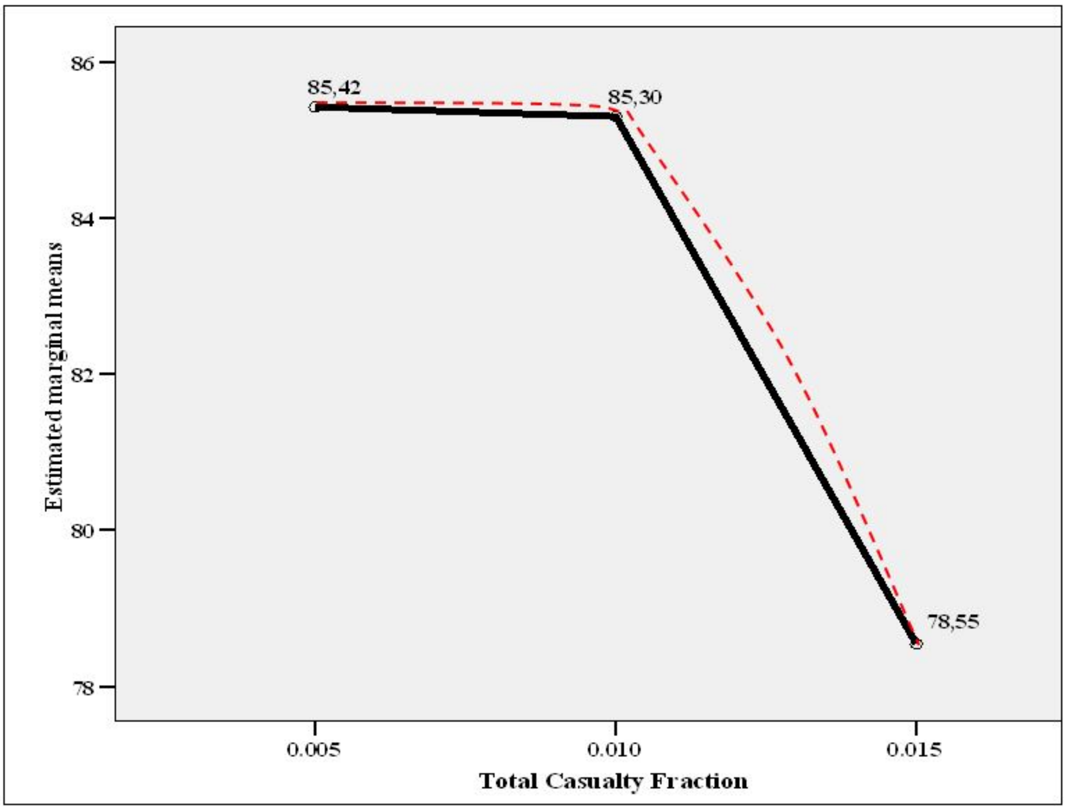

Figure 7. The effect of victim fraction on mean waiting time for treatment (min.) in observation room

5. CONCLUSIONS

The preparedness and planning activities related to emergency aid services in the event of disaster are important in saving lives and returning to normal life conditions quicker after the disaster had occurred. In Turkey, many large cities, including İzmir, are under the significant risk of a major earthquake. Emergency rescue activities in such situations can be modeled analytically; however it is challenging to solve analytical models constructed for the problems with realistic dimensions.

With this aim in mind, a unified simulation model was developed for transporting casualties to medical care centers and their treatment processes in a disaster situation. Victim transportation and treatment processes are clearly linked and it is essential to analyze these two processes simultaneously to achieve optimum results. We propose a simulation model, which includes both victim transportation and treatment, and perform verification& validation steps. The model was developed in accordance with manual and rules, and a case study using real life data from Bornova was presented. The proposed simulation model can easily be adapted to different locations with adaptation of relevant data.

Based on the real data, for Bornova district of İzmir City, this model was applied to the transportation processes to medical treatment locations (treatment points to be built in the site, hospitals) and also treatment processes in the hospitals after a major earthquake.

Based on the results of the extensive experimental design performed, using statistical methods, following were computed: ambulance waiting times, waiting times for treatment in trauma and observation rooms in hospital emergency departments and how various parameters affect these times.

We find that for Bornova case, differences in ambulance waiting times among different regions are substantial. Either a new distribution of ambulances or additional ambulance waiting locations are recommended.

When the number of the triage staff is increased to reduce waiting time for triage operation, the number of medical personnel should be increased accordingly or alternative treatment areas should be constructed parallel to increasing number of triage staff, since it was discovered that waiting times in trauma and observation rooms will also increase. Total casualty fraction also affects waiting times, and at the maximum level of this factor, large number patients lose their lives in the triage and treatment queues are at the large numbers. Significant effects of total casualty fraction were found both on ambulance waiting time and waiting time for treatment. Therefore the analysis of the results shows that before the actual disaster, any activity which will decrease the total casualty fraction will be highly effective in reducing total loss.

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Appendix 1: Data for Figure 3

		Total casualties		
		Low	Medium	High
# of ambulances	46	17.209	26.206	39.906
	51	15.886	24.191	36.838
	59	13.977	21.285	32.412

		Total casualties		
		Low	Medium	High
# of ambulances	46	21.094	32.122	48.914
	51	19.472	29.652	45.154
	59	17.133	26.089	39.729

		Total casualties		
		Low	Medium	High
# of ambulances	46	14.389	21.911	33.365
	51	13.282	20.226	30.800
	59	11.687	17.796	27.100

		Total casualties		
		Low	Medium	High
# of ambulances	46	17.637	26.857	40.898
	51	16.281	24.792	37.753
	59	14.325	21.814	33.217

		Total casualties		
		Low	Medium	High
# of ambulances	46	8.948	13.626	20.749
	51	8.260	12.578	19.154
	59	7.268	11.067	16.853

		Total casualties		
		Low	Medium	High
# of ambulances	46	10.968	16.702	25.434
	51	10.125	15.418	23.478
	59	8.908	13.566	20.657

		Total casualties		
		Low	Medium	High
# of ambulances	46	12.139	18.485	28.149
	51	11.206	17.064	25.985
	59	9.860	15.014	22.863

		Total casualties		
		Low	Medium	High
# of ambulances	46	14.880	22.658	34.504
	51	13.736	20.916	31.851
	59	12.085	18.403	28.024

		Total casualties		
		Low	Medium	High
# of ambulances	46	8.072	12.292	18.719
	51	7.452	11.347	17.279
	59	6.556	9.984	15.203

		Total casualties		
		Low	Medium	High
# of ambulances	46	9.895	15.067	22.944
	51	9.134	13.909	21.180
	59	8.036	12.238	18.636