

SIMULATING RURAL EMERGENCY MEDICAL SERVICES DURING MASS CASUALTY  
DISASTERS

by

KENDRA SULLIVAN

B.S., Kansas State University, 2008

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Industrial and Manufacturing Systems Engineering  
College of Engineering

KANSAS STATE UNIVERSITY  
Manhattan, Kansas

2008

Approved by:

Major Professor  
Dr. Malgorzata Rys

# **Copyright**

KENDRA SULLIVAN

2008

## Abstract

Emergency Medical Systems (EMS) are designed to handle emergencies. Fortunately, most emergencies faced have only one patient. The every day system is not designed to respond to emergencies in which there are many casualties. Due to natural disasters and terrorist attacks that have occurred over the past decade, mass-casualty disaster response plans have become a priority for many organizations, including EMS. The resources available for constructing such plans are limited. Physical simulations or practices of the plan are often performed; however, it is not until a disaster strikes that the capabilities of the plan are truly realized. In this paper, it is proposed that discrete-event simulations are used as part of the planning process. A computer simulation can test the capability of the plan under different settings and help planners in their decision making.

This paper looks at the creation of a discrete-event simulation using ARENA software. The simulation was found to accurately simulate the response to the Greensburg tornado that occurred May of 2008. A sensitivity analysis found that the simulation results are dependent upon the values assumed for *Volunteer Injury Rate*, *Injury Level*, *Information Dissemination Rate* and *Transportation Decision* variables.

When a disaster occurs, the local resources are overwhelmed and outside aide must be called in. Decision rules for when to request more outside ambulances and when to release them to send them home are evaluated. The more resources that are made available, the quicker patients receive medical care. However, when outside ambulances are called in, they are putting their home area at risk because it no longer has complete (or any) ambulance coverage. As the percent of coverage decreases, the amount of time that victims spend waiting for ambulances also decreases. Many decision rules were evaluated, resulting in various combinations of ambulance wait times and average percent coverage. It is up to Disaster Planners to determine how much of an additional wait can be assumed by the disaster victims to prevent outside districts from taking on unwarranted risk of low coverage.

# Table of Contents

List of Figures .....	viii
List of Tables .....	x
CHAPTER 1 - Introduction .....	1
1.1 Differences in Rural and Urban Ambulance Systems .....	2
1.2 Differences in Steady-state and disaster Ambulance Systems .....	3
1.3 Definitions .....	7
1.3.1 Rural.....	7
1.3.2 Mass Casualty or Disaster.....	7
CHAPTER 2 - Literature Review .....	9
2.1 Modeling Emergency Medical Systems .....	9
2.1.1 Covering Models.....	10
2.1.2 Queuing Approaches.....	11
2.1.3 Simulation Models.....	11
2.2 Validity of Emergency and Disaster Response Plans .....	12
2.2.1 Studies of previous disasters do not always provide good data for future incidents ...	13
2.2.2 Communication systems are often unreliable during mass casualty events .....	13
2.2.3 Non-requested Ambulances and Emergency Workers will show up to help.....	14
2.2.4 Much of the search and rescue efforts are preformed by survivors and other untrained volunteers .....	15
2.2.5 A small portion of casualties will arrive at the hospital via ambulance and many will not have been through decontamination and field-triage.....	15
2.2.6 The walking injured and minor casualties arrive first .....	17
2.3 Modeling Disaster Response .....	17
2.4 EMS Statistics.....	18
2.4.1 Time on scene .....	18
CHAPTER 3 - Methods .....	20
3.1 Assumptions.....	20
3.1.1 Assumption 1 – Non-disaster related call volumes.....	20

3.1.2 Assumption 2 – Number of people killed or injured is population dependent .....	21
3.1.3 Assumption 4-Number of people killed or injured is dependent upon the percentage of destruction.....	22
3.1.4 Assumption 3-The disaster strikes at a single moment, causing all injuries to occur simultaneously .....	23
3.1.5 Assumption 5-Priority of providing medical care.....	23
3.1.6 Assumption 6-The amount of time that it takes for ambulances and private vehicles to travel to and from the scene is dependent upon the percentage of destruction.....	24
3.1.7 Assumption 7-Many of the survivors will assist in search and rescue efforts and some of them will be injured in the process .....	25
3.1.8 Assumption 8-The area being modeled is a rural area, only one Level 1 Trauma Center is considered.....	25
3.1.9 Assumption 9-The area can be divided into regions, with all times calculated from the center of the region .....	25
3.2 Modeling Details.....	26
3.2.1 Model Input.....	26
3.2.1.1 Region Population.....	26
3.2.1.2 Hospitals and Trauma Levels.....	26
3.2.1.3 Distances and Travel Time .....	26
3.2.1.4 Ambulances and their location.....	27
3.2.1.5 Victims Decision Making Process .....	28
3.2.1.6 Level of Destruction and Severity of Injuries.....	29
3.2.1.7 Normal Call Volume.....	30
3.2.2 Model Design.....	31
3.2.2.1 Entities .....	32
3.2.2.2 Victims .....	33
3.2.2.3 How to seek help.....	37
3.2.2.4 Triage Station.....	40
3.2.2.5 Private Transport to Hospital .....	41
3.2.2.6 Normal Call Volume.....	41
3.2.2.7 Load Ambulances .....	42

3.2.2.8 Ambulance Transportation.....	44
3.2.2.9 EMS Director Decisions .....	46
3.2.2.10 Request Out of District Ambulances .....	47
3.2.2.11 Out of District # .....	48
3.2.2.11 Set up Field Station.....	49
3.2.2.12 Release Out of District Ambulances.....	50
3.3 Running the Simulation .....	51
CHAPTER 4 - Results and Model Validation .....	53
4.1 System Setup.....	53
4.1.1 Regions, Distances and Population.....	53
4.1.2 Normal Calls .....	55
4.2 Sensitivity Analysis .....	61
4.2.1 Total Ambulance Time .....	61
4.2.2 Ambulance Wait Time.....	64
4.2.3 Time to arrival at hospital .....	68
4.3 Comparison to actual events.....	71
4.4 Evaluating Decision Rules.....	73
Request Rule 1, Releases Rule 2.....	76
Request Rule 1, Releases Rule 3.....	78
Request Rule 2, Release Rule 1 .....	80
Request Rule 3, Releases Rule 1.....	82
Request Rule 4, Releases Rule 1.....	84
Request Rule 5, Releases Rule 1.....	87
Conclusions about Decision Rules.....	88
CHAPTER 5 - Conclusions .....	90
5.1 Improvements .....	92
Model Inputs and Variable Values .....	92
General Model .....	93
Decision Rules .....	93
5.2 Areas for Future Research .....	93
Bibliography .....	95

Appendix A - Calculations for Tornado Destruction Percentages..... 100

## List of Figures

Figure 1-1 Generalized Process Map of Steady State Ambulance Response.....	5
Figure 1-2 Generalized Process Map of Ambulance Disaster Response.....	6
Figure 3-1 Graph of relationship between Percent Destruction and Percent Injured/killed.....	22
Figure 3-2 Regression Analysis of Percent Injured/killed versus Percent Destruction.....	23
Figure 3-3 Routing of victims through simulation model .....	32
Figure 3-4 Confidence Intervals for the mean delay time for Level 3 injuries.....	35
Figure 3-5 Delay times for Level 3 injuries      Figure 3-6 Delay times for Level 2 injuries .....	35
Figure 3-7 Confidence Intervals for the mean delay time for Level 2 Injuries .....	36
Figure 3-8 Histogram of delay times for Level 1 injuries .....	36
Figure 3-9 Confidence Intervals for the mean delay time for Level 1 Injuries .....	37
Figure 4-1 Map of Kiowa County      Table 4-1 Value of <i>Region Population Variable</i> .....	53
Figure 4-2 Locations of Ambulance Districts Participating in MERGe.....	57
Figure 4-3 Grouping of Ambulance Districts for Simulation.....	59
Figure 4-4 DOE Factors and their levels .....	61
Figure 4-5 ANOVA table for Total Ambulance Time (Output from MiniTab).....	62
Figure 4-6 Histogram of Total Ambulance Time Residuals.....	62
Figure 4-7 Main Effects Plot for Total Ambulance Time.....	63
Figure 4-8 Interactions Plot for Total Ambulance Time .....	64
Figure 4-9 ANOVA table for Ambulance Wait Time (Output from MiniTab).....	65
Figure 4-10 Histogram of Ambulance Wait Time residuals.....	66
Figure 4-11 Main Effects Plot Ambulance Wait Time.....	67
Figure 4-12 Interaction Effects Ambulance Wait Time .....	67
Figure 4-13 ANOVA table for Time to arrival at hospital (Output from MiniTab).....	68
Figure 4-14 Histogram of Time to arrival at hospital residuals.....	69
Figure 4-15 Main Effects Plot Time to arrival at hospital .....	70
Figure 4-16 Interactions Plot for Time to arrival at hospital .....	70
Figure 4-17 Simulation statistics compared to Greensburg statistics, all factors at Level 2 .....	72



Figure 4-18 Simulation statistics compared to Greensburg statistics, all factors at Level 2, Injury Severity at Level 1 .....	72
Figure 4-19 Results from Simulating Request Rules and Release Rules .....	75
Figure 4-20 Box-plot of the Differences from paired T-test on Ambulance Wait time .....	77
Figure 4-21 Box-plot of the differences from paired t-test on average percent coverage .....	77
Figure 4-22 Box-plot of the differences from paired T-test on Percent of time that coverage is less than 50% .....	78
Figure 4-23 Box-plot of the differences from paired T-test on average ambulance wait time.....	79
Figure 4-24 Box-plot of the differences from paired T-test on average percent coverage.....	79
Figure 4-25 Box-plot of differences from paired T-test on average percent of time coverage is less than 50% .....	80
Figure 4-26 Box-plot of difference for paired t-test of average ambulance wait time .....	81
Figure 4-27 Box-plot of differences for paired t-test of average percent coverage.....	81
Figure 4-28 Box-plot of differences for paired t-test of average percent of time coverage is less than 50% .....	82
Figure 4-29 Box-plot of difference for paired t-test of average ambulance wait time .....	83
Figure 4-30 Box-plot for difference of paired t-test of average percent coverage .....	84
Figure 4-31 Box-plot for difference of paired t-test of average percent of time coverage is less than 50%, the resulting p-value for the difference in means was 0.001 .....	84
Figure 4-32 Box-plot of differences for paired t-test of average ambulance wait time.....	85
Figure 4-33 Box-plot of differences from paired t-test of average percent coverage.....	86
Figure 4-34 Box-plot of differences from paired t-test of average percent of time coverage is less than 50% .....	86
Figure 4-35 Box-plot for differences from paired t-test of average ambulance wait time .....	87
Figure 4-36 Box-plot of differences from paired t-test of average percent coverage.....	88
Figure 4-37 Box-plot of differences from paired t-test of average percent of time that percent coverage is less than 50% .....	88

## List of Tables

Table 2-1 Time on scene statistics (Morrisey and Ohsfeldt 1996) .....	19
Table 3-1 Severity of Injury Levels .....	29
Table 3-2 Values assigned to attributes in Distances ASSIGN block .....	38
Table 3-3 Comparison of Gamma distribution to statistics for trauma time on scene .....	45
Figure 4-1 Map of Kiowa County      Table 4-1 Value of <i>Region Population</i> Variable .....	53
Table 4-2 Value of <i>Time</i> variable .....	54
Table 4-3 Value of Percent Destruction Variable.....	54
Table 4-4 Value of Trauma Levels Variable .....	55
Table 4-5 Value of Normal Call Severity      Table 4-6 Value of Location Normal Calls .....	56
Table 4-7 MERGe Ambulance Districts (Region III EMS) .....	58
Table 4-8 Values for Out of District Ambulances .....	60
Table 4-9 Ambulances by simulation district      Table 4-10 OD # Ambulances variables .....	60
Table 4-11 Decision Rules.....	74
Table 5-1 Summary of Percent Destruction statistics.....	100

## **CHAPTER 1 - Introduction**

Emergency Medical Systems (EMS) are designed to handle emergencies. Fortunately, most emergencies that they face have only one patient. The every day system, which I will call the steady-state system, is not designed to be able to respond to emergencies in which there are many casualties. Due to natural disasters and terrorist attacks that have occurred over the past decade, mass-casualty disaster response plans have become a priority for many organizations, including EMS. The resources available for constructing such plans are limited. Physical simulations or practices of the plan are often performed; however, it is not until a disaster strikes that the capabilities of the plan are truly realized. In this paper, it is proposed that discrete-event simulations are used as part of the planning process. A computer simulation can test the capability of the plan under many different settings and help planners to determine where holes in their plan exist.

To demonstrate the possibilities of simulating disaster plans, this paper will show how the ambulatory response to mass casualty tornados can be simulated. According to the Federal Emergency Management Agency (FEMA), tornados are nature's most violent storms. Approximately 1200 tornadoes touch down within the United States each year (NOAA Storm Prediction Center). While only a small percent of these tornados have been deadly, when a tornado strikes a highly populated area, the result can be devastating. On February 5<sup>th</sup> 2008 a storm that produced sixty-seven tornados ripped across Kentucky, Tennessee, Arkansas, and Alabama killing 55 people (Kenning 2008). In the most severely hit area, Macon County Kentucky, fourteen people were killed and approximately 70 were seriously injured. Many others were described as "walking wounded" (Greenway 2008).

In 2007, 81 people died from injuries that resulted from a tornado. Twelve of these deaths occurred when a tornado wiped out the small, rural town of Greensburg, KS. Along with the twelve deaths, there were over 90 people requiring medical assistance. The town's medical resources, including a small hospital were destroyed by the storm, leaving the town completely reliant upon neighboring communities for assistance (Ablah 2007).

## **1.1 Differences in Rural and Urban Ambulance Systems**

When it comes to emergency management, there are many differences between that of rural communities and those of larger urban areas. The challenges faced by rural EMS services are different than those faced by urban ambulance systems. In rural areas the population served by a single ambulance district is much smaller than that in urban areas. Conversely, the area covered by a single ambulance district is much larger for rural areas. Rural ambulance services struggle with being able to provide quick emergency response to their constituents because they may have to travel thirty plus miles in one direction to reach their patients. The nearest hospital for many rural patients is not in their small town, but in the nearest city. Also, the call volumes in some areas are so low that a regular staff of paramedics cannot be maintained. In these cases the entire emergency medical staff may be volunteers and will have to be called in from their work or homes to respond to emergency situations.

While the lower population density of rural areas presents problems in the funding of ambulance systems and in enabling quick responses, it does not rule them out from the threat of mass casualty events. There are many causes of mass casualty incidents, with terrorism being only one of them. Nature provides many threats to rural areas. Tornados, floods, fires, earthquakes, all of these may lead to a disaster that will injure or kill a large number of people. Industrial accidents also occur in rural areas. When a mass casualty event occurs in a rural community, they have much fewer resources at their disposal. For example, in 2007 New York City had an average of 968 ambulances available for use at a given time, answering an average of 3,253 calls per day (FDNY Vital Statistics 2007). In Greeley County, Kansas the picture is completely different. A single ambulance staffed by volunteers serves its residents that are spread across 778 square miles of land. The ambulance responds to an average of 120 calls per year, including standbys and transfers (McCain 2007). This is one call per three days. It would not take a very large disaster to overwhelm the Greeley County ambulance system, where as in New York City, resources could be quickly reallocated to accommodate an increased demand in a specific sector of the city.

Along with differing demand patterns, characteristics of the population-base differ from rural to urban settings, such as: age, gender, race, severity of illness, and types of medical problems. These can add to the differences that will be seen in the response to and outcome of emergencies (Stripe 1991). The research for this thesis will focus on the response to mass-

casualty events that occur in rural areas, a definition of rural and mass-casualty is presented in Section 1.3.

## **1.2 Differences in Steady-state and disaster Ambulance Systems**

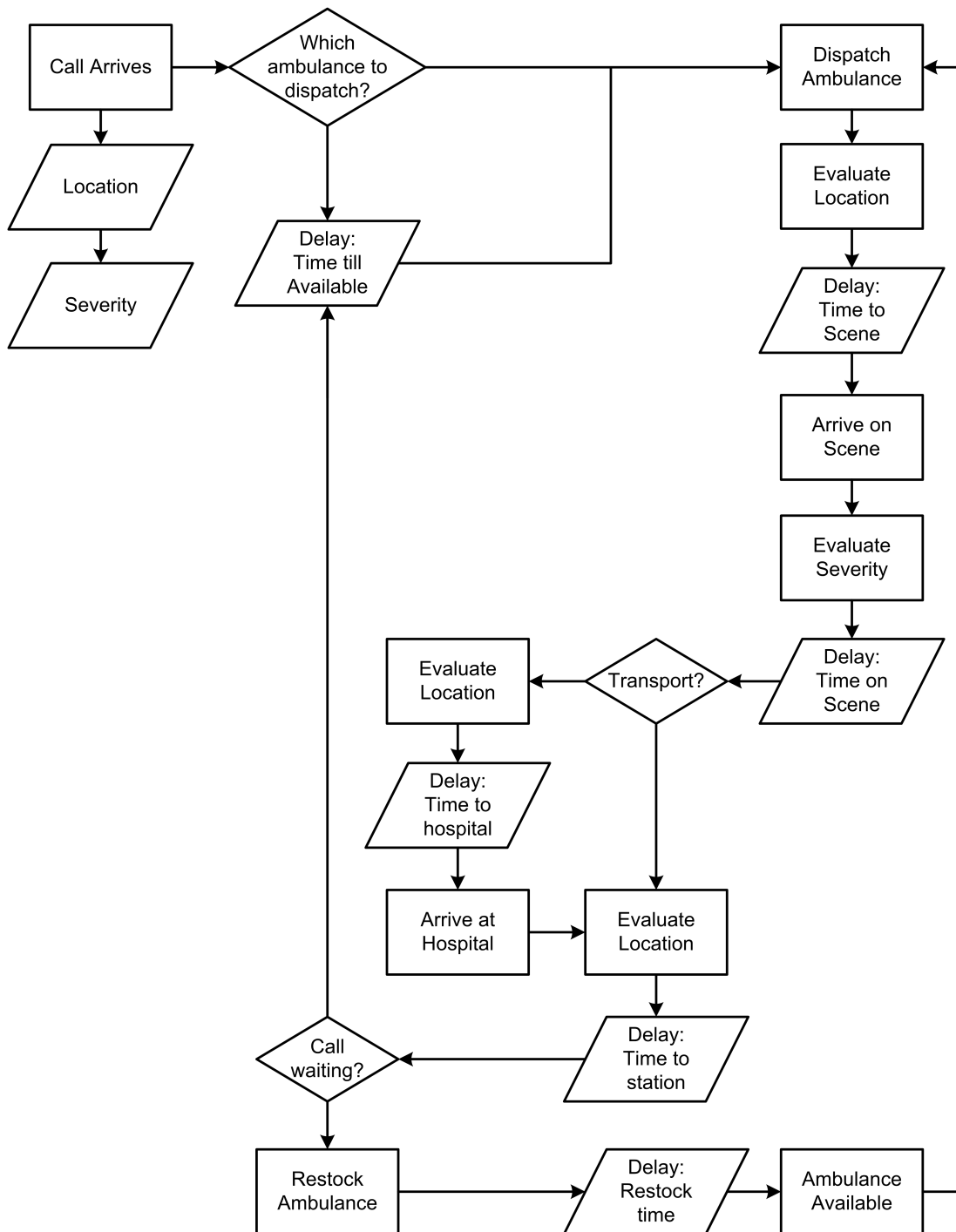
The emergency medical system that emerges in a mass-casualty or disaster situation is greatly different than the steady-state ambulance system. Under normal conditions, ambulance systems rely on a dispatch routine that looks something like this: A phone call is received stating that someone needs medical attention. An address is taken and an ambulance is dispatched to that location. Paramedics perform first-aid and necessary life support functions at the scene. If the patient requires additional medical assistance, they are loaded into the ambulance and transported to the appropriate hospital. The hospital is generally contacted prior to arrival to let them know that the patient is coming. The patient is unloaded at the hospital and the ambulance returns to their station to restock their ambulance and await another call. The general process for a steady state ambulance system is mapped in Figure 1-1. In an emergency situation, the routine can look much different.

Each EMS department has their own disaster plan, just as it has its own methods for every-day operation. The type of disaster will greatly influence the response. However, in general, there are a couple of things that may make the disaster system significantly different then the steady-state system. The first, and most obvious one, is the increased number of patients that need help. Second, there is the possibility that some of the resources that are considered standard, such as electricity, water, and telephone capabilities, may not be available due to the disaster that caused the mass-casualty incident. The loss of power and running water will virtual shut down hospital emergency departments (Bohonos 1999). Depending on the type of disaster, roads may be left impassable. To handle the increased flux of patients, help is generally called in or voluntarily supplied from surrounding areas. This adds the challenge of establishing and maintaining communication. In disaster situations, resources are overwhelmed. In many cases, ambulance drivers may convert to a scoop and run strategy where they do not wait on a call from the patient, but go to the site of the disaster, find injured people, and transport them to the hospital as quickly as possible. The level of on-scene first aid and triage may vary greatly compared to that which would be seen under normal conditions. Also, make-shift first aid and triage stations may be created to prove as a gathering point for patients and to perform pre-

hospital care. A generalized process map of an ambulatory disaster response system can be seen in Figure 1-2.

There have been many papers written about what makes a good safety plan. A disaster plan is most easily adhered to when it maintains normal daily routine as much as possible (Breakey 1988). Many resources are available that assist disaster planners in creating their disaster response plan. The National Incident Management System, a program released in 2004 by the Department of Homeland Security as a part of FEMA, gives guidelines and training to assist in the creation of local response plans. The focus of this thesis is not on the development of the response plans, but on the use of discrete-event simulation as a tool to evaluate response plans for the purpose of determining in what areas the plan is lacking and how the plan will likely hold up in response to specific situations.

# 911 Call Response Process For Steady State System



**Figure 1-1 Generalized Process Map of Steady State Ambulance Response**

# Victim Routing to Medical Attention during mass casualty event

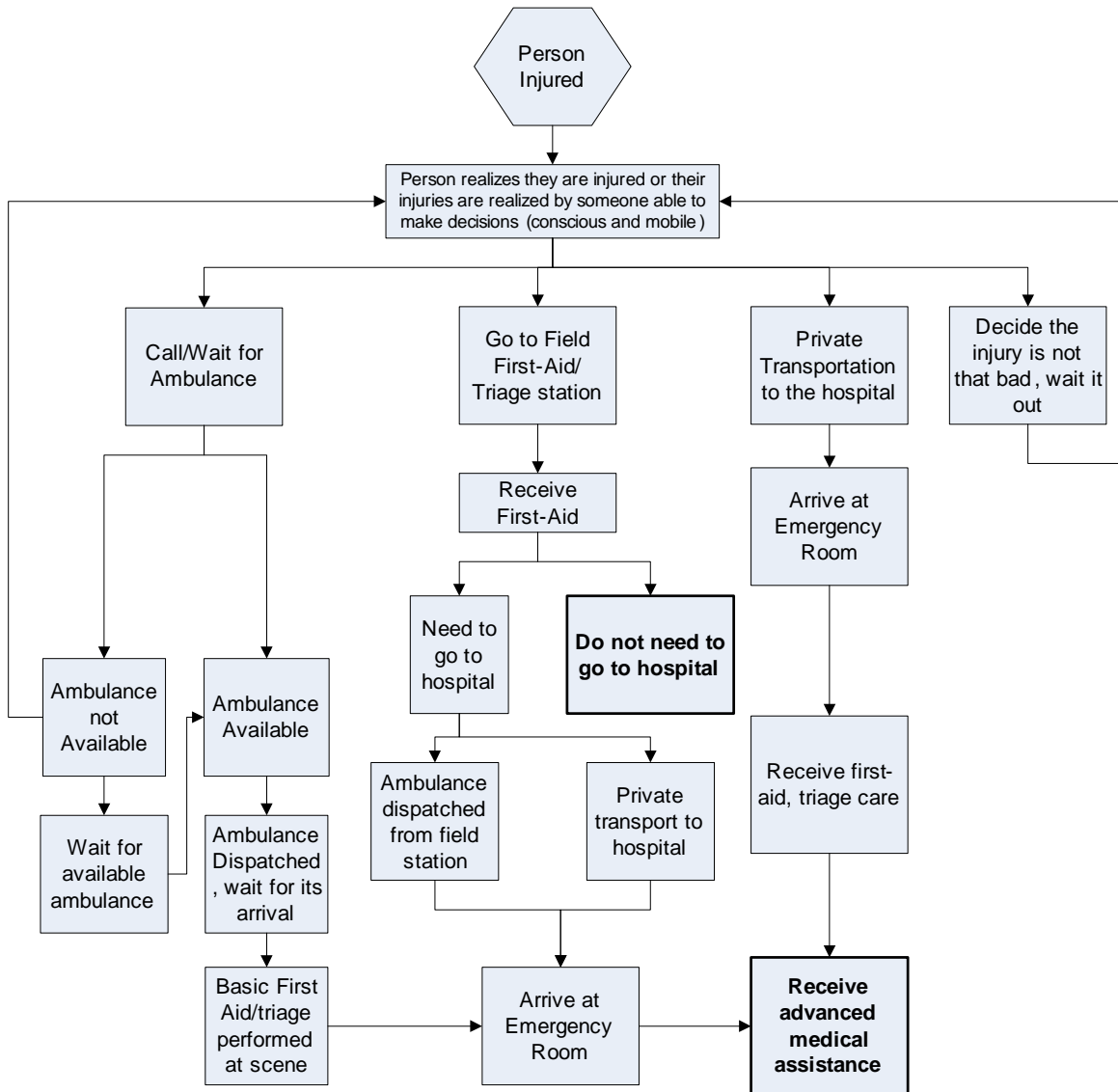


Figure 1-2 Generalized Process Map of Ambulance Disaster Response



## **1.3 Definitions**

### ***1.3.1 Rural***

Different agencies have different definitions of the word “rural”. This leads to an interesting debate about how to define the word. The exact definition is not critical to this research. EMS systems are as different as the communities that they are serving. There is not a clear line in population or population density at which the struggles of the system change from those of rural problems to those of urban problems, rather it is a continuum. The United States Department of Agriculture (USDA) defines rural as being “open country and settlements with fewer than 2,500 residents”. This may be true from an agricultural standpoint, but from a medical standpoint, it takes significantly more than 2,500 people to support an urban medical system. The Office of Management and Budget (OMB) defines rural as anywhere that is not within a metropolitan area, with a metropolitan area being a city with at least 50,000 people. More complex systems of determining rurality have been established over the years (Ricketts 1998).

For the purpose of this paper, rural EMS systems are going to be defined as those that are responsible for covering a large, sparsely populated region. Such counties may have a city of over 50,000 people; however, if there are rural areas with a significant number of people who do not have easy, immediate access to the medical services of that city, then the area shall be considered rural. This is often the case for counties that border metropolitan areas or those containing small cities (50,000-100,000 people) and then several small towns or farming communities.

### ***1.3.2 Mass Casualty or Disaster***

There are many differing definitions for mass casualty and disaster situations. In his paper, “Disaster Epidemiology”, Noji states, “From a public health perspective, disasters are defined by what they do to people; otherwise, disasters are simply interesting geological or meteorological phenomena. What might constitute a disaster for one community might not necessarily be considered a disaster in a different community.” (Noji 1996). There are many types of disasters that exist. Often, they are broken down into two categories, man-made disasters and natural disasters. For the purpose of this thesis, these categories are virtually irrelevant. Issues such as the suddenness and duration of the force that is resulting in medical emergencies and the size of the area over which this is occurring is more critical in simulating

the emergency response. While bombings are man-made disasters, and tornados are natural disasters, they are in many ways similar from the medical response perspective. Both generally result in a very dense disaster area where nearly all of the people in the area are affected. Injuries due to shrapnel, flying debris and falling objects are prevalent. These situations are sudden and results in many people being injured within just a few minutes, leaving many people needing care at the same time.

A good definition of mass casualty incident is provided by the Virginia Office of Emergency Medical Services. They state that a mass casualty incident is “one which generates more patients than available resources can manage using routine procedures” (Green, 2000). This is the definition that will be used for both mass casualty and disaster throughout this paper. The two words may be used interchangeably.

## **CHAPTER 2 - Literature Review**

Over the years, a great deal of research has been conducted on improving the efficiency of medical care, including studies done on ambulance systems. Most of these studies revolved around urban medical systems. Rural medical systems; however, have many unique characteristics that leave some of the findings of these inapplicable to them. Assignment problems and ambulance location problems that can be very complex in urban systems, may become trivial in very rural areas where there is only one ambulance and it responds to very few calls per year. There are still many similarities between rural systems and urban systems, and thus the knowledge gained by studies performed on urban systems is beneficial in studying rural systems. Both rural and urban areas face the challenge of dealing with budget constraints. All ambulances face the challenge of responding rapidly to calls. For urban areas, the issue may be traffic and low speed limits. For rural areas, large coverage areas force ambulances to travel a long distance to reach many of the patients.

### **2.1 Modeling Emergency Medical Systems**

Emergency Medical Systems have received a great deal of attention from the operations research (OR) community since the 1960's. Much of this has stemmed from a group of OR analysts that worked at New York's RAND Institute during the late 1960's and the 1970's. Their research was strong in both theory and in application and covered Emergency Medical Systems, Fire Systems and police operations (Goldberg 2004). Some of the areas of research that have been prominent over the years include:

1. The location of fixed position fire stations and ambulance bases
2. The dispatching of vehicles to calls
3. The number and type of vehicles, staff, and equipment
4. The use of flexible locations for un-dispatched ambulances known as System Status Management

Most of the models that have been created follow some of the same basic rules. First, instead of looking at every possible location that a call could arrive from, cities are broken into small areas called “zones”. All of the calls originating from the zone are assumed to occur from the center of the zone and travel times and coverage are calculated accordingly. The more zones a model considers, the higher the accuracy of the expected coverage due to an increased accuracy in the actual time that it will take to arrive at the call location. Three basic types of error that result from the creation of zones were defined by Hillsman and Rhoda in 1978.

A errors—errors in distance measurement for the call since the original call location is not the location of the aggregated calls,

B errors—errors in distance measurement due to not knowing the true location when a vehicle or facility is located at an aggregation zone,

C errors—errors in dispatching due to not knowing the correct distance from vehicles or bases to calls in aggregated zones.

As technology improves and computing power increases, the size of each zone can be decreased, decreasing the effect of such errors. The reduction and elimination of these errors have been discussed by Current and Schilling [1987], Hodgson and Neuman [1993] and Erkut and Bozkaya [1999].

### ***2.1.1 Covering Models***

Many modeling techniques have been used to solve these problems. Church and Revelle (1974) created a maximal covering model that sought to solve the problem of where to locate a fixed number of ambulances. With this model, a zone is considered covered if it is within the travel time of an ambulance. It does not take into consideration that this ambulance may be faced with a large demand and thus not always available for dispatch to a call. This was then improved upon by Daskin and Stern in 1981 to maximize the number of zones that were covered by more than one vehicle. Still, these models lacked the flexibility that many urban emergency medical systems needed. These models required that the demand for an area be constant over time and that an ambulance remain at the same base location that it is originally assigned to. In urban areas where the population in a zone of the city at a given time of day is based on whether it is residential, commercial, or industrial, the demand in an area can be very dependent upon time. In an attempt to solve this problem in order to develop a decision support system for locating

ambulances with Louisville, KY, John F. Repede develops what he calls the TIMEXCLP model, which incorporates time variation into the maximal expected coverage location problem (1994).

Set covering problems have also been used. The first was developed by Toregas et. al. in 1971. The model minimizes the cost by finding the minimum number of ambulances that can cover all of the zones. As with the maximal covering models, there is no regard to the demands of each of the zones or whether an ambulance is busy or available for use.

For all of these models, the demand is assumed to be deterministic, as well as the travel times and the service time. All calls are responded to with the same equipment; there is not a distinction between calls that may need Advanced Life Support or calls that could be satisfied with Basic Life Support units. Also, as mentioned before, there is no regard for busy vehicles. This will result in inflated expected values of system coverage.

ReVelle has continued to work on improving this area and has expanded models to address many of these problems (Schilling, ReVelle, Cohen, and Elzinga 1980; ReVelle, Schweitzer, and Snyder 1996; ReVelle and Hogan, 1999).

### ***2.1.2 Queuing Approaches***

The most notable queuing approach is the hypercube models created by Larson (1974, 1975). In this model, there are a set number of vehicles serving the area. They are then located through out the area to minimize the total expected travel distance to serve all demands. It takes into consideration which vehicles are preferred to respond to each call and whether that vehicle is busy. In order to do this, the state of the system must be kept track of and the rule for responding to a call is dependent upon the state the system is currently in. The model has  $2^N$  states, making the problem NP-Complete. Larson continued to build and extend this model to include locate-allocate heuristics (Larson 1979, Brandeau and Larson 1986). In 1996 Marcianov and ReVelle used queuing theory to create a realistic location model for emergency systems. A more complete review of queuing theory approaches can be found in Jia et al (2007).

### ***2.1.3 Simulation Models***

The popular use of simulation in terms of modeling Emergency Medical System modeling is for model validation. Once a set of possible solutions is obtained from simple set covering or maximum covering problems, a simulation can be created to evaluate each of the solutions. City specific models have also been created, the first of these being for New York

City (Savas 1969). Another was produced by Erkut and Polat in 1992 to minimize the total travel time and the percent of calls not served within a permissible time in Istanbul, Turkey. Another model was created for Richmond, VA and is detailed by Zaki, Cheng, and Parker in 1997. Repede and Bernardo use simulation to develop a decision support system for locating emergency medical vehicles in Louisville, KY. Their TIMEXCLP covering model provides inputs for a simulation. If the results of the simulation meet the requirements, then the locations are used, if they do not, the TIMECLP is re-run and the new locations simulated. This iterative process continues until the simulation output meets the pre-determined requirements. Simulation models are only currently created to validate solutions obtained by other models or for the use of a specific city. Little research seems to have been done into general simulation models that can be adapted to serve a wide range of locations.

## **2.2 Validity of Emergency and Disaster Response Plans**

Creating and practicing emergency and disaster response plans is something that has become very common in our society today. Every organization from hospitals to schools to retail stores and churches has considered and planned out how they will respond in the face of a disaster. Likewise, city, county, state, and national disaster response plans exist that detail how medical services will respond in the face of a crisis. EMS personnel have practiced this response as with other emergency workers, but on what basis are such plans created? Is there evidence that these plans will work, or that the situations that they are mitigating are likely to unfold in the manner that the plan is geared for? Many of the assumptions made during emergency planning are invalid (Auf der Heide 2006). The reasons these assumptions are invalid are explained in the following sections (2.2.1-2.2.6). Some of the common assumptions that are often incorrect are:

1. Studies of previous disasters provide good data for future incidents.
2. Communication systems will remain intact.
3. Only requested ambulances and emergency response workers will respond.
4. Search and rescue is completed by emergency response workers such as fire fighters, police officers, paramedics, and other trained personnel.
5. Casualties will arrive at the hospital via ambulance and will have been through decontamination and field-triage.
6. The most serious casualties will arrive first.

### ***2.2.1 Studies of previous disasters do not always provide good data for future incidents***

The nature of disaster studies makes the collection of good, meaningful data very difficult. There is no way to perform controlled experiments. In most disasters you cannot choose the location and there is a single-impact occurrence. It is not possible to control the countless variables that exist. Studies are generally performed after the fact and it is difficult to compare the pre-disaster data to post-disaster data due to changes in population in the area due to death, relocation, or an influx of relief workers. Medical networks often have a very difficult time keeping track of patients and recording the very information that would be useful in post-disaster analysis. When a study was done on the tornado that struck Oklahoma City in 1999, pre-hospital care was not documented for 14.3% of the patients (May 2002). Since not all data is collected, most data that exists rely on post-disaster surveys and accounts of what occurred, which is less accurate than data that would be collected at the time of the disaster. All of these factors make it very difficult to collect accurate disaster data and difficult to extrapolate that data to determine how a similar disaster may affect a different community. Better record keeping and data collection during disasters would improve the ability to provide accurate data as references for disaster plans.

### ***2.2.2 Communication systems are often unreliable during mass casualty events***

Communication is a key element in successfully implementing and carrying out most plans. Unfortunately, in many disaster situations, communication networks fail. Their failure may be due to several factors. In a disaster such as a tornado or hurricane, telephone lines and cellular phone towers may be taken out, leaving telephone communication impossible. Even if the phone lines and cellular phone towers remain intact, in disaster situations, these lines are quickly flooded and rendered useless. Radio communication will experience the same flooding of use, leaving them overloaded and ineffective for performing the needed communication. Another problem that is often overlooked when it comes to communication is communication with ambulances and workers who come from outside to the normal ambulance district. Not all districts use the same type of radios, and the varying frequencies of these radios may make it impossible for outside ambulance and staff to use their equipment to communicate with local officials, dispatchers, and hospitals. In a Kansas tornado that struck on April 26, 1991 ambulances were directed to the closest hospital rather than the one with the proper capabilities.

Communication had broken down due to neighboring counties having different radio frequencies. On top of this, the radio frequencies overloaded, preventing field crews from communicating with the hospitals to notify them of incoming patients. Miscommunication resulted in ambulances being dispatched to locations where no patients were found or where patients had already been treated or transported via other means (Prillman 1993). Even in the modern day of cellular phones, this problem is not eliminated. Most EMS systems still rely on radios for most of their communication. The use of cellular phones is unlikely to have a large impact on the results found in this study for two reasons. First, the focus of this paper is on rural areas, which often have limited cellular phone coverage to begin with. Second, just as radio frequencies can quickly become overloaded, so can cellular phone networks. Except in the case of cellular phones, you not only have emergency workers flooding the network, but citizens as well.

All of these communication problems should be considered in disaster planning, as they are likely to occur. Preventative measures, such as having extra radios on hand to issue to outside responders or collaborating with nearby districts to ensure that radios are compatible may decrease the chance that the communication system will fail (Auf de Heide 2006).

### ***2.2.3 Non-requested Ambulances and Emergency Workers will show up to help***

When a disaster occurs, everyone assumes that there will be a shortage of resources. Nearby communities may send non-requested aid under this assumption and the assumption that it is better to have extra people than not enough. In many cases, the initial reports broadcasted via media and scanners may be inaccurate, and thus a surplus of aid may arrive. While this does not initially sound like a problem, it can lead to confusion and a breakdown of the emergency plan. An example of this occurred when an F3 tornado hit a camp ground at Pine Lake in Alberta on July 14, 2000. There were over 254 people at the campgrounds at the time. A campground provides little shelter that can sustain a tornado. A total of 12 people were killed by the storm, and another 130 were injured. Upon hearing of the storm, ambulances were dispatched from all over the region. Hospitals fully enacted their disaster response plans, clearing as many beds as possible and calling in all available staff. However, due to many people opting for private transportation to hospitals, and the large quantity of ambulances that responded, a line of ambulances sat idle waiting for a patient to transport. Many of these ambulances had left their



home region without an ambulance to respond to local emergencies. The scene-to-hospital times were 1-2 hours, resulting in many doctors and nurses waiting around for patients that would never arrive, or would arrive much later than was expected. At one hospital there were three doctors and three nurses waiting at each bay, many of whom never saw a tornado victim (Sookram 2001). Auf der Heide says that non-requested ambulances are often not integrated into the response plan. They may have no communication with local officials and are thus not utilized efficiently. He suggests that if the disaster is localized, that the area is immediately barricaded off so that all incoming emergency vehicles are directed to a check-in area where they are briefed and possibly given a radio so that they can communicate with local personnel (Auf der Heide 2006).

#### ***2.2.4 Much of the search and rescue efforts are preformed by survivors and other untrained volunteers***

Search and rescue efforts begin long before trained responders arrive at the scene. It has been documented in many cases that the survivors are the first to begin search and rescue (Sookram 2001). They are on the scene when the disaster occurs and thus begin search and rescue efforts almost immediately. The survivors often have information about the last location of the missing, and are thus very beneficial in aiding the trained emergency workers in the search and rescue effort. However, they do not tend to approach the search in a systematic fashion that will in result in finding as many people as quickly as possible and they do not plan ahead and foresee future problems that their actions may create (Auf der Heide 2006).

The initial impact is not the only occasion when people are injured and need medical attention. Up to 50% of injuries from tornadoes may be sustained in the rescue and recovery period. Minor injuries such as lacerations, foot punctures, sunburn, and heat injuries are some of the common post-tornado injuries (Bohonos 1999).

#### ***2.2.5 A small portion of casualties will arrive at the hospital via ambulance and many will not have been through decontamination and field-triage***

A majority of the minor injuries are transported to hospitals via private transportation. These victims often begin arriving at the hospitals within 5 to 30 minutes of the disaster by foot, by personal vehicles, by buses, by taxis, and by other non-ambulatory forms of transportation (Bohonos 1999). In some cases, the arrival of the first victims in the ER is the first notification

that officials receive of the disaster (Golec and Gurney 1977). The portion of patients that arrive via ambulance seems to vary on a disaster by disaster basis. This number is typically less than half of all casualties that arrive at the emergency department of a hospital (Arboleda, Abraham and Lubitz 2007). Auf der Heide (2006) presents statistics given by the Disaster Research Center which says that only 54% of disaster victims are initially transported by an ambulance. Examples are given of an earthquake in the San Francisco bay area where only 26% of the earthquake injured patients arriving at the hospital were transported by ambulance. When the Murrah Federal Building was bombed in Oklahoma City, only 33% of the victims were transported by ambulance. When the World Trade Center was attacked, only 6.8% of the 7,364 patients were transported by ambulance. With only a small portion of patients arriving via ambulance, triage and decontamination that is usually performed pre-hospital is often not occurring. Even when decontamination and field triage locations are established, they are frequently bi-passed by victims. This may be because they are unaware of their existence or because they feel as though they will receive better care at the emergency room.

Generally, by the time doctors and nurses are sent to the tornado site to aid victims, there are few people requiring assistance. The dispatch of doctors and nurses to the tornado site has little impact on morbidity or mortality (Bohonos 1999). This is not always the case. In the case of the Greensburg tornado of May 4, 2007, a triage center was the only way to connect many victims with the help that they needed. The town was demolished, with 95% of the homes and businesses in this 1,400 person town being destroyed (Ablah 2007). Along with the houses, emergency response resources, hospitals, power lines, telephone lines and cellular phone towers were demolished. Roads were blocked and many impassible. The closest hospital was 30 minutes away at the Pratt Regional Medical Center. Victims did not have the capability of calling for help and with many cars destroyed and impassable roads, private transportation was not an option for many. A triage center was established in the parking lot of a grocery store and was used as the base for search and rescue and medical aide. Ambulances from as far as 100 miles away came to the scene and transported victims from the triage station to hospitals in Pratt, Dodge City and Wichita (Potter 2007).

### ***2.2.6 The walking injured and minor casualties arrive first***

The first victims to arrive at the emergency department are usually those with minor injuries, or those classified as “walking-injured”. The more serious injuries arrive later, generally within one to four hours after the tornado occurred (Bohonos 1999). Those suffering the worse injuries many be covered in piles of debris, unconscious and unable to seek help, or may require ambulance transportation. This results in it taking longer for the severely injured to reach the emergency room. Hospitals and emergency workers may plan on prioritizing patients and treating them in the order of the severity of their injuries; however, since all casualties do not arrive at the emergency department at the same time, emergency personnel are often busy with minor injury patients when the severely injured arrive (Mandelbaum 1966, Golec 1977, Auf der Heide 2006).

## **2.3 Modeling Disaster Response**

Disaster response is greatly different than emergency response, and thus requires different modeling techniques. There has been much less research done in this area, compared to that of steady-state emergency responses systems; however, with the changing times, this area of research has become more and more necessary and prevalent. Communities every where are preparing disaster response plans, and many of them would like to asses the capabilities of these plans. Arboleda, Abraham, and Lubitz (2007) have taken a System Dynamics simulation technique to show how a system will respond to disaster situations and the impact that the condition of the infrastructure systems will have on the ability to respond.

Gong and Batta (2007) have research methods and rules for the allocation and reallocation of ambulances during a disaster relief operation. They suggested that responders only respond to what they call “casualty clusters”, or areas that have at least N casualties waiting for ambulance assistance. This is due to the fact that in disaster situations, it is likely that multiple people will be loaded into the same ambulance for transport. They then develop a dynamic model for the growth and decay of clusters over time.

Jia, Ordonez, and Dessouky (2005) developed a model for determining the location of medical services for large-scale emergencies. This is different from models that determine the location of hospitals or fire stations or ambulance bases. This does not consider the staffing of medical personnel or ambulances that are used daily; rather it is used for determining the

location within a region at which a large stock of medical supplies will be kept for easy dispatch to any disaster or large-scale emergency that occurs within that region or through out the nation.

## **2.4 EMS Statistics**

### ***2.4.1 Time on scene***

Time on scene is defined as the interval between when the ambulance arrives at the scene to when they depart the scene. This time may be affected by many factors, including the type of injury, the severity of the injury, the size of the patient, and the location of the patient (do they have to be carried up or down stair or extricated from a vehicle?). No research was found that determined the individual effect of any of these factors. However, several papers have been written that analyze the overall average time on scene for trauma patients. In a tornado, nearly all of the injuries sustained will be trauma injuries, thus these studies are useful.

Grossman, Kim, et al (1997) looked at the differences in rural and urban response to “major trauma” victims. He looked at 452 calls from one EMS district that contained both rural and urban areas. He found that the average time on scene was 21.7 minutes for rural areas and only 18.7 minutes for urban areas. 98% of the transports in the study were provided by non-volunteer, Advanced Life Support (ALS) equipped ambulances. When Grossman looked at the effect of the severity of trauma injury on the time on scene, he found that there was no significant effect. It should be noted, that he was only looking at “severe trauma” victims, thus the relationship between severity of injury and time on scene may be found to be significant if all trauma patients were considered and not just those who were classified as severe.

The effect of ALS care on the time on-scene was evaluated by Eckstein, Chan, et al (2000). The use of two different airway intervention techniques on trauma patients were evaluated to determine if they had a significant affect on the mean time on-scene. The difference in on-scene times was found to be insignificant. This study was performed in a large metropolitan area, with 54% of the victims having gunshot wounds or stabbing wounds. The conditions of the study are very different than those that would be experienced by a rural EMS system responding to tornado victims, and thus the results of this study will not be taken into consideration when determining time-on-scene estimates for the simulation.

Morrisey and Ohsfeldt, et al (1996), analyzed the ambulance trip reports for rural trauma patients who were served by the EMS system that provides services to 12 rural counties

surrounding Augusta, Georgia. 2,416 trip reports were examined, each of which indicated “trauma” as the clinical area. The minutes at the scene were evaluated in two separate groups. The first group was of 2,416 patients and it was those who were alive upon arrival and still alive when the ambulance departed the scene. The second group, consisting of 36 patients, was of the patients who were dead on ambulance arrival or who died while the paramedics were on the scene. The times for these two groups are significantly different. For the “alive” group, the mean time on scene was found to be 13.9 minutes with a standard deviation of 7.9. For the “dead” group, the mean was 38.7 minutes with a standard deviation of 28.3. The overall mean time on-scene was 14.3 minutes. A summary of the time on scene statistics given in this paper can be found in Table 1.1. Of the trauma calls that ambulances report to, nearly 8% of the patients were not transported. Information on the location of patients and the frequency of various medical techniques performed is also given.

**Table 2-1 Time on scene statistics (Morrisey and Ohsfeldt 1996)**

	n	Mean	St.Dev	Mean by Percentile		
				50th	75th	90th
<b>Alive</b>	2416	13.9	7.9	12	18	23
<b>Dead</b>	36	38.7	28.3	31	58	87

## **CHAPTER 3 - Methods**

A computer simulation was constructed for a generalized disaster response plan. Changes to the simulation may be necessary to adapt the simulation to the response plan of a specific county; however, this model shows that discrete-event simulation can be used to model the response of an ambulance system to a mass-casualty event such as a tornado. Such simulations could prove very useful to emergency planners, as they seek to determine the weaknesses of their plan and methods for improving it. Physical simulation of several different disaster response plans to determine which is the best is impractical and could lead to confusion within the Emergency Personnel as to how they should actually respond when a disaster occurs. Thus, it is difficult for disaster response planners to know what policies are most appropriate for their region and how different policies would affect their ability to respond to various situations. In this section, the assumptions made are discussed and then the details of how the simulation model was created.

### **3.1 Assumptions**

In creating the simulation many assumptions had to be made. Not all of the assumptions would hold true for every EMS system since policies and emergency response procedures vary greatly between EMS departments. The following basic assumptions were made. Other assumptions are discussed in the Modeling Details section as the model is explained.

#### ***3.1.1 Assumption 1 – Non-disaster related call volumes***

The rate at which ambulances will be called for non-disaster related emergencies will be the same as the EMS department experiences during the steady-state, non-disaster time period. This call volume is assumed to be constant throughout the day, and to be unaffected by the disaster. It is assumed that the dispatch location and areas that were not directly hit by the disaster still have telephone capabilities, and thus it is possible for people who are not in the disaster zones to call for an ambulance. Those who are within the disaster zone but who have an emergency that is not disaster induced will be treated in the same manner as those who were

injured in the disaster. It is assumed that they may not have telephone capabilities or any means of calling for assistance. It is also assumed that they will not seek assistance at a triage or field station or opt for private transportation, but rather that they will seek out ambulance transportation. Non-disaster related calls that are not in the disaster zone will be responded to by the first available local ambulance.

### ***3.1.2 Assumption 2 – Number of people killed or injured is population dependent***

It is assumed that the number of people who are killed or injured by a disaster is dependent upon the number of people in the area. To say that all F-5 tornados kill 20 people or F-3 tornados kill 12 people, is an obvious error, as the number of people that will be affected will depend on the number of people that are in the area at the time of the disaster. When a tornado hits a highly populated area, it is common sense to assume that more people will be injured and in need of medical assistance than if the same strength of tornado was to hit a sparsely populated region. Determining the number of people that will be injured in a storm is difficult. Most reports of tornados tell you how many people were injured and what the strength of the tornado was, but few tell how many people were in the area when the tornado struck. Resources such as the Tornado History Project ([tornadohistoryproject.com](http://tornadohistoryproject.com)) provide the beginning and ending longitude and latitudes for thousands of tornados as well as statistics on deaths and injuries; however, even knowing the beginning and ending points of the tornado, it is difficult to determine the population that was in the path of the storm. Tornados are not constrained to moving in a straight line, and with some of the most powerful tornadoes staying on the ground for as many as 40 to 50 miles, the number of people and small towns that may or may not have been directly in its path is hard to determine. Also, when looking at population data and census statistics the numbers are generally given for entire cities or counties. If only a small portion of a county is affected by the tornado, then it is not appropriate to use the entire county population as a means of comparison. Measurements such as population density could be used and compared to the area of the tornado's path; however, population density can vary greatly within a county and is thus very dependent upon the region within the county. Such specific population statistics are not available for most counties.

### 3.1.3 Assumption 4-Number of people killed or injured is dependent upon the percentage of destruction

It is intuitive that the greater the destruction that a tornado generates, the more people who will be injured or killed. More destruction means more debris flying through the air and more buildings or parts of buildings collapsing and thus more opportunities for people to be injured. There are very few tornados for which data on the percentage of destruction is available; however, data was found for a few. The percentage of destruction and the percentage of people injured or killed were compared and it was found that the relationship between the two can be modeled using the equation: Percent Injured/Killed =  $38.4344 - 1.12210 \cdot \text{Percent Destruction} + 0.0083036 \cdot \text{Percent Destruction}^2$ . A graph of the five data points that were used to find this relationship is shown in Figure 3-1. A p-value of 0.003 was calculated for the regression model, allowing the model to be accepted at a 95% confidence level. The details of the regression analysis can be found in Figure 3-2. An explanation of how the data points were obtained can be found in the Appendix A. Due to the quadratic relationship, this model does not work well for values of percent destruction that are lower than the 62% minimum point used in creating the model. For low values of percent destruction, the percent of injuries increases, which is the opposite of what actually occurs. For this reason, if the percent destruction is less than 63, the quadratic relationship is abandoned and a linear relationship is adopted. This relationship is a line between the points (0,0) and (63, 0.7). The slope of this line is 0.001111.

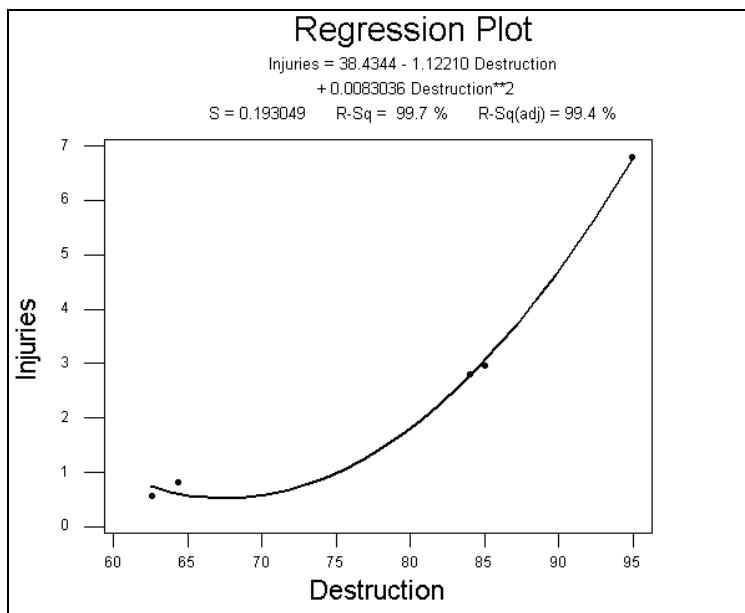


Figure 3-1 Graph of relationship between Percent Destruction and Percent Injured/killed



REGRESSION ANALYSIS: Percent Injuries vs. Percent Destruction					
Injuries = 38.4344 - 1.12210 Destruction + 0.0083036 Destruction**2					
S = 0.193049		R-Sq = 99.7 %		R-Sq(adj) = 99.4 %	
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	2	24.8869	12.4434	333.892	0.003
Error	2	0.0745	0.0373		
Total	4	24.9614			
Source	DF	Seq SS	F	P	
Linear	1	21.4103	18.0878	0.024	
Quadratic	1	3.4765	93.2850	0.011	

**Figure 3-2 Regression Analysis of Percent Injured/killed versus Percent Destruction**

***3.1.4 Assumption 3-The disaster strikes at a single moment, causing all injuries to occur simultaneously***

The length of time that a tornado is on the ground and bringing destruction on a community can vary. For some tornados, it may be a matter of minutes, for others it may be closer to an hour. However, while the tornado is on the ground in an area, there is little that can be done for the victims. Emergency personnel must wait until the tornado has lifted or passed through their community before they can begin search and rescue and provide medical care. For this model, it is assumed that all of the injuries occur simultaneously at the beginning of the model. Thus, all of the victims are generated at time zero in simulation time. This can be thought of as the first instant that the tornado has lifted or passed on far enough for people to come out of hiding and begin seeking help. Obviously, not all victims begin to seek help at the same moment. Some who have minor injuries may first look for their loved ones. Others may be stuck under piles of debris or trapped in basements. A delay between when the injury is sustained, TNOW=0 and when the medical help is sought exists and is modeled based on the severity of the injury.

***3.1.5 Assumption 5-Priority of providing medical care***

In mass casualty situations, the ideal situation would be for medical officials to be aware of all injuries at the beginning and thus be able to treat the most severely injured victims first.

This has not been found to be the case. Generally, the first people to seek medical attention are those who suffer minor injuries and are capable of seeking help on their own, also referred to as the walking-injured (See section 2.2.6). Prioritization still must occur; however, it can only consider the victims who are currently seeking help, not those who emergency workers do not know about. This may be because they have not yet gained consciousness or been found by an emergency worker or other capable person. It is assumed that emergency workers will aid the most severely injured of those currently seeking medical assistance first and that once an emergency worker begins assisting a victim, they cannot leave that victim to help another victim—regardless of the severity of their injury. It is assumed that ambulance crews will not spend their time on uncovering or transporting dead bodies, as those responsibilities will be left up to other emergency workers such as firefighters, police, etc.

***3.1.6 Assumption 6-The amount of time that it takes for ambulances and private vehicles to travel to and from the scene is dependent upon the percentage of destruction***

The greater the level of destruction that results from a tornado, the more debris there will be covering roads and blocking ambulances from coming in and out of the area. Entire sections of road may be ripped from the ground by a tornado, thus leaving it impassable. The speed at which vehicles can travel is greatly dependent upon the amount of debris that is covering the roads. Gong, Jotshi, and Batta made a similar assumption that speed of travel is dependent on the percentage of damage in their research on emergency vehicle response to earthquakes (2004). The ambulances in the model were given the velocity:  $\text{Max}(1-(\text{Percent Destruction}(\text{Field Location},1)/100),0.2)$ , where the velocity is the amount of time that it takes the ambulance to travel one unit length from the distance matrix. As the percentage of destruction approaches 100%, the travel speed of the ambulances approaches zero. The Max function is used to prevent ambulance velocities from reaching 0 and thus putting rescue efforts at a stand still. As emergency crews work to clear roads and make them more passable, it is intuitive that the travel speeds should increase. The model takes this into account by decreasing the value of percentage of destruction over time.

***3.1.7 Assumption 7-Many of the survivors will assist in search and rescue efforts and some of them will be injured in the process***

As is explained in section 2.2.4, it is common for the survivors of a disaster to assist in the search and rescue efforts. This can be dangerous, as it may involve sifting through piles of debris, working in intense heat, or lifting heavy objects. As a result, those who are assisting in rescue efforts are at risk of becoming injured and needing medical attention. This is taken into consideration in the model by having a percentage of the survivors (based on the user input variable *Willingness*) participate in rescue efforts. A percentage of these are then injured based upon the variable *Volunteer Injury Rate*.

***3.1.8 Assumption 8-The area being modeled is a rural area, only one Level 1 Trauma Center is considered***

This is a rural area, thus only one Level 1 Trauma Center will be considered. Most rural communities are a great distance from a Level 1 Trauma center and it is very rare that a rural community would have the luxury of having more than one Level 1 Trauma Center in close proximity. “Hospital 1” in the simulation will always be considered the closest Level 1 trauma center.

***3.1.9 Assumption 9-The area can be divided into regions, with all times calculated from the center of the region***

It is not practical or possible to consider the exact location every person within the county and their relationship to EMS services and the hospital. Thus, the county or EMS district is divided into several regions. It is assumed that all demand originates from the center of the region. All travel times are based upon the time that it takes to reach the center of the region. The population for each region must be input into the model. The disaster is unlikely to affect all regions equally. The disaster may strike only one region, or multiple regions may be affected. Regions that are not affected by the disaster may still need ambulance support to cover the every-day demand or ailments and injuries that were independent of the disaster.

## 3.2 Modeling Details

A discrete-event simulation was created using Arena 10.0. The modeling details are explained in this section. Many assumptions had to be made about time relationships and the amount of time that different processes would take. These assumptions will be explained and suggestions for further research into improving the accuracy and validity of these numbers will be made.

### 3.2.1 Model Input

#### 3.2.1.1 Region Population

The number of people that are in each region must be input into the model. This is done through changing the initial values for the variable, *Region Population*. This is an  $r \times 1$  matrix, where  $r$  is the number of regions in the model.

#### 3.2.1.2 Hospitals and Trauma Levels

The system must be initialized with the trauma level for each of the hospitals. It is assumed that Hospital 1 is the closest Level 1 trauma center. The other hospitals could be Level 2 or Level 3 trauma centers. The type of hospital is indicated through the variable *Trauma Levels*. This is an  $h \times 1$  matrix, where  $h$  is the total number of hospitals that are being simulated. The trauma level of a hospital will be taken into consideration when the ambulance drivers are determining which of the hospitals to take victims to.

#### 3.2.1.3 Distances and Travel Time

A variable called *Time* is used to store a matrix of the amount of time that it takes to get from each region to each of the other regions and each hospital. If there are  $r$  regions, and  $h$  hospitals, then the dimension of this matrix will be  $r \times (r+h)$ , like the following example for 3 regions and 3 hospitals and 2 other districts from which to pull resources.

The values in the matrix represent the distance in minutes of travel time during normal conditions. These times will then be adjusted based upon the *Percentage of Destruction* to determine the actual amount of time that it takes to go from one point to another.  $Time(1,1)$  is the average time that it takes to get from a point in Region 1 to the center of Region 1.  $Time(2,1)$  is the average time that it takes to get from the center of Region 1 to the center of

	<b>Region 1</b>	<b>Region 2</b>	<b>Region 3</b>	<b>Hospital 1</b>	<b>Hospital 2</b>	<b>Hospital 3</b>
<b>Region 1</b>	Time(1,1)	Time(1,2)	Time(1,3)	Time(1,4)	Time(1,5)	Time(1,6)
<b>Region 2</b>	Time(2,1)	Time(2,2)	Time(2,3)	Time(2,4)	Time(2,5)	Time(2,6)
<b>Region 3</b>	Time(3,1)	Time(3,2)	Time(3,3)	Time(3,4)	Time(3,5)	Time(3,6)

Region 2. All of these times are during normal conditions. The EMS ambulance station and the triage center will each be assigned a value  $1-r$ , to indicate which of the regions they are located in. The EMS ambulance station's location must be input by the user before the model runs. This is done by setting the initial value of the variable *Ambulance Station* to the number of the region that it is located in. The location of the triage center is determined by the model based upon the number of injuries in each of the regions.

Along with the *Time* matrix, the distances must be input into the *Ambulance.Distance* distance set for the ambulance transporter. This only requires the distances between each of the regions and each of the hospitals.

Another matrix *Times for OD Ambulances* is used to indicate the time from each of the out of district facilities to each of the local regions. This is an  $r \times d$  dimensional matrix, where  $r$  is the number of regions (local) and  $d$  is the number of other districts that resources can be brought in from.

	<b>OD 1</b>	<b>OD 2</b>
<b>Region 1</b>	Time(1,1)	Time(1,2)
<b>Region 2</b>	Time(2,1)	Time(2,2)
<b>Region 3</b>	Time(3,1)	Time(3,2)

### 3.2.1.4 Ambulances and their location

The number of ambulances available and their locations must be input into the model. The "Transporter-Advance Transfer" table allows you to change the total number of ambulances and the initial location of the ambulances. There are essentially two types of ambulances, local ambulances and out of district ambulances. They are both modeled by the same *Ambulance* transporter; however, their initial status is different. The local ambulances will initially be positioned at the EMS station and will be active transporters. It is assumed that out of district ambulances will report to the triage station before beginning service, thus their initial position is the triage station. Their initial status is Inactive. The out of district ambulances will be activated

once their assistance has been requested and they have been delayed for the appropriate time that it would take for them to travel to the triage center from their home location. It is assumed that out of district (OD) regions are ordered from closest to farthest, thus OD 1 is the closest district to the local region.

Keeping track of which ambulances are being dispatched to aid in the disaster relief and which are not requires the creation of several variables, some of which require user input for the initialization. The number of ambulances that each outside district has is indicated through the variable *OD # Total Ambulances*, where the # is replaced by the number of the district (e.g. *OD 1 Total Ambulances*). *OD # Ambulances* is used to keep track of which of the ambulances belong to each of the districts. The input into this variable is the number of ambulances that precedes the district's first ambulance on the ambulance list. For example, if there are 8 ambulances, with the first 4 being local ambulances, then two from District 1 and two from District 2, then *OD 1 Ambulances* would be set equal to 4 and *OD 2 Ambulances* would be set equal to 6. The rest of the ambulance variables should not be changed by the user.

### ***3.2.1.5 Victims Decision Making Process***

The decisions that the victims make greatly impact the performance of the EMS system. Some of these decisions may be based off of local biases towards one option over another. One decision that has to be made is whether those who are not injured will aid in the search and rescue efforts or not. The *Willingness* of the survivors may vary greatly from one region to another. The number of people who decide to help will directly impact the number of people who are injured while helping and thus the demand on the medical systems. The initial value of the *Willingness* variable should be input as a whole number between 0 and 100. This can be thought of as the percentage of survivors who are willing to help with the rescue efforts.

In order for a victim to decide to go to the Triage Station, they must know that the Triage Station exists. The variable *Information Dissemination Rate* indicates how many people are aware of the Triage Station. Communities that have highly visible emergency response plans in place so that citizens know where a triage location would be established at a may have a very high *Information Dissemination Rate*. If the triage location is in a highly visible area, say right along a main road that would have to be used to exit the area to reach a hospital, the *Information Dissemination Rate* may also be high (Perry and Lindell 2003). The value of the information

dissemination rate should be between 0 and 100 and corresponds to the total percentage of victims who will be aware of (not necessarily choose to go to) the Triage location.

**3.2.1.6 Level of Destruction and Severity of Injuries**

The level of destruction greatly impacts the number of people that will require medical attention. The magnitude of the disaster that is being simulated is input through the variable *Percent Destruction*, which forms an  $r \times 1$  matrix, which indicates the percentage of destruction for each region,  $r$ . These values should be between 0 and 100.

The number of people injured is related to the percent of destruction. The severity of their injuries must then be determined. For this model, injury severity is divided up into three categories. Level 1 injuries are those that require medical attention, but that are not severe enough that they will cause the patient to be admitted to a hospital. This group is made up of “walking-injured”. Level 2 injuries are more severe and will require more immediate attention. Patients with Level 2 injuries are critical enough that the patient may not be capable of seeking medical attention on their own and will require hospital admission. Level 3 injuries are fatal injuries that will likely result in the loss of life. Level 3 injuries can be divided into two groups. The first group contains those whose injuries result in nearly instantaneous death. These victims will not require or receive medical care. The second group is made up of those who are fatally injured, and will die if they are not administered medical attention quickly. Table 3-1 summarizes the injury levels.

**Table 3-1 Severity of Injury Levels**

Severity of Injury Level	Explanation of Injury Levels
1	Minor injuries, walking injured, no admission to hospital
2	Severely injured, may be incapable of seeking medical assistance, will require hospital admission
3	Deaths. Fatally injured, injuries will likely result in death either immediately or prior to arrival at the hospital.

The variable *Injury Severity* is a  $3 \times 1$  matrix that contains the percentage of the victims who fall into each of the three injury levels. The value in each of the cells should be between 0 and 1 and the sum of the three cells should equal 1. Consistent data was not available for the severity of injuries caused by tornado disasters. Reports that contained information about the

injuries sustained were inconsistent in how they measured and reported their data and thus the results could not be aggregated to determine an overall expected value for tornado disasters. Sensitivity analysis was performed on this variable to determine how the system is affected by various *Injury Severity* values. See section 4.2. The default value that has been entered for this variable is (0.7, 0.2, 0.1) or in matrix form:

Level 1 Injury	0.7	
Level 2 Injury	0.2	
Level 3 Injury	0.1	

The *Volunteer Injury Rate* and *Volunteer Injury Severity* can both be changed as well. The volunteer injury rate determines the percentage of those volunteering who are going to be injured. It is a value between 0 and 100 that is representative of the percentage of those volunteering who will be injured. The default value for this is 1, indicating that 1% of the volunteers will suffer injuries. As with the *Injury Severity*, a sensitivity analysis was performed on this variable (Section 4.2). The *Volunteer Injury Severity* is similar to the *Injury Severity*, except it is used only for those hurt during the relief efforts. While many injuries occur during rescue efforts, they do not tend to be as severe of injuries (Bohonos 1999). The default value for *Volunteer Injury Severity* is (0.7, 0.3, 0), or in matrix form:

Level 1 Injury	0.7	
Level 2 Injury	0.3	
Level 3 Injury	0.0	

### 3.2.1.7 Normal Call Volume

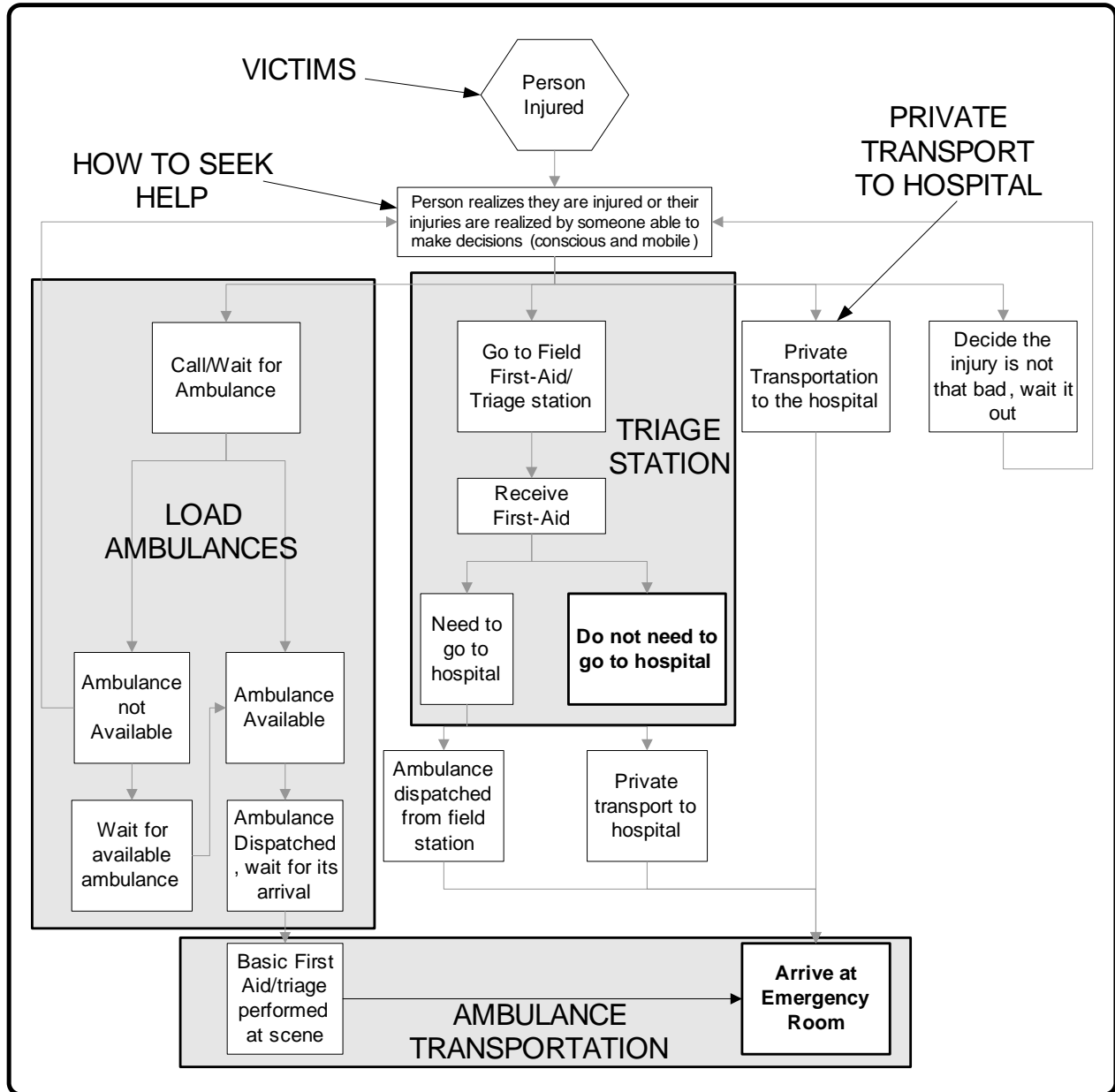
Even during the disaster, people will still have non-disaster related medical emergencies, for instance an elderly person having a stroke. Thus, it is assumed that the normal call volume for the EMS services will continue through out the disaster and thus those calls will be added on top of the disaster calls. It is assumed that the “normal call volume” calls arrive according to an exponential distribution with an inter-arrival time of *Time Between Normal Calls*, which should be initialized by the user to contain the historic average time between calls. Along with the average time between calls, the severity of the injuries must also be assigned. This should also be established from the ambulance services historical data and assigned via the *Normal Call Severity* variable. Like the *Injury Severity* and the *Volunteer Injury Severity*, the *Normal Call Severity* is a 3 x 1 matrix containing values between zero and one that sum to one. The location



of the normal calls must also be initialized, via the variable *Location Normal Calls*. This is an  $r \times 1$  matrix and like *Normal Call Severity*, this matrix contains values between zero and one that sum to one.

### ***3.2.2 Model Design***

There are two major parts to the simulation, the simulation of what is occurring directly to the victims, and the simulation of the decisions that are going on behind the scenes. Figure 3-3 shows how each of the sections of the simulation model that deal with the victims fits into the overall process.



**Figure 3-3 Routing of victims through simulation model**

**3.2.2.1 Entities**

Two different entities are used within the simulation model, each with its own function. The majority of the entities in the model are “*victims*” or people who were in the region(s) that the disaster hit. *Victims* are assigned attributes such as location and severity of injury to represent

their need for emergency medical assistance. A victim entity is also used to represent people who call for an ambulance with a medical emergency that is unrelated to the disaster. These are the people that would be calling on a regular day, independent of the occurrence of a disaster. Like the other *victims*, they are also assigned the location and severity of injury attributes.

A single “*Local EMS Official*” Entity is created to run the decision process that must be done by the Local Emergency Director. This entity goes through a series of branch blocks and evaluates the state of the system and makes changes and alterations to the system as needed.

### 3.2.2.2 *Victims*

A CREATE block exists for each of the regions within the model. It creates “*Region Population(n, 1)*” victim entities, where *n* is the region number. Not all of these victims are actually injured; they are simply the people who are in the region at the time of the disaster. Once created, each of the victims is assigned a location and their station (*m*) is set to the appropriate value. A 2-way by expression DECIDE block is used to determine what the Percent Destruction in the area is. This determines which of DECIDE blocks is used to determine if the victim is injured or not. If the Percent Destruction is greater than or equal to 63% then the following quadratic expression is used to determine the percent of victims injured, which is the percent true in the DECIDE block:

$$38.4344 - 1.12210 * Percent\ Destruction(1,1) + 0.0083036 * Percent\ Destruction(1,1) * Percent\ Destruction(1,1)$$

If the *Percent Destruction* is less than 63%, then the following linear expression is used as the percent true:  $(0.001 * Percent\ Destruction(1,1))$

This utilizes the regression formula that was found to represent the relationship between the percent of destruction and the percent of people who are injured or killed, which was discussed in section 3.1.3 and ensures that small values of percent destruction will not result in a larger than appropriate percent injury.

Those that are not injured will go to the “Rescue Efforts” Section of the simulation. The number of injured victims from each region is then counted before all of the injured are sent through an assign block to assign them *Victim Number* and *Severity of Injury* attributes. *Severity of Injury* is assigned by using the expression:  $DISC(Injury\ Severity(1,1),1,Injury\ Severity(1,1)+Injury\ Severity(2,1),2,1,3)$ ; where *Injury Severity* is a variable containing a 3 x 1

matrix representing the percentage of each type of injury. This matrix was explained in section 3.2.1.6.

Once a *Severity of Injury* is determined, the *Expiration Time* attribute must be assigned. The *Expiration Time* tells how long the victim can survive without hospital care. The system will periodically compare the victims *Expiration Time* to TNOW, if the *Expiration Time* is less than TNOW, the victim will be assumed to have died. The DECIDE block named “Fatally Injured?” is used to separate the victims by *Severity of Injury* level. Those who have a *Severity of Injury* equal to 3 are the fatally injured. As explained in section 3.2.1.6, some of these will die almost instantaneously; others will survive the initial impact, but are in a grave condition and will die if they do not receive medical assistance very quickly. The DECIDE block “Dead on Scene?” splits the Level 3 injures into two groups. In the first group, 90% of the victims are found dead on scene and are thus counted and then disposed from the system; they will not require medical assistance. The other 10% are in desperate need of medical attention and are assigned an expiration time based on the distribution: TRIA(60,120,240), indicating that the expiration time of the victim will be between one and six hours, with the most likely value being two hours. These numbers were established based on the report by Bohonos (1999) that indicates that the more severely injured patients generally arrive at the Emergency Room one to four hours after the disaster occurs. Victims with a Level 2 injury level are assigned an *Expiration Time* of 1440, which is equal to one day, their injuries are critical; however, they are not likely to die if they do not receive immediate medical attention. Victims with a Level 3 injury level have injuries that are not life threatening, thus their *Expiration Time* is set to a very large number (50,000) so that TNOW will never be greater than their *Expiration Time*.

The number of each type of injury is then counted, and the entity goes to a DELAY block which represents the amount of time that it takes the victim to begin seeking medical assistance. This delay may be due to the victim being trapped under debris, unconscious, or preoccupied with assisting family members and other victims. If the victim is severely injured, then it may be the amount of time that it takes for someone who is capable of seeking help for them (conscious and mobile) to find them.

The length of the delay is given by the expression: EXPO(Delay Time(Severity of Injury,1)). Giving delay times that are exponentially distributed with a mean of “Delay Time(Severity of Injury, 1)” Where “Delay Time” is an Expression containing the following

values: [Gamma(25,1.25), Gamma(45,1.5), Gamma(50,2)]. The first value corresponds to the delay time for those with level 1 injuries, the second to level 2 injuries, and the third to level 3 injuries. Figures 3.4-3.9 show the approximate delay times produced by such a distribution. These values were found by performing 5 replications with 500 observations within each replication. Gamma distributions were sought that would give delay times that line up with the observations about patients arrivals made by Bohonos (1999).

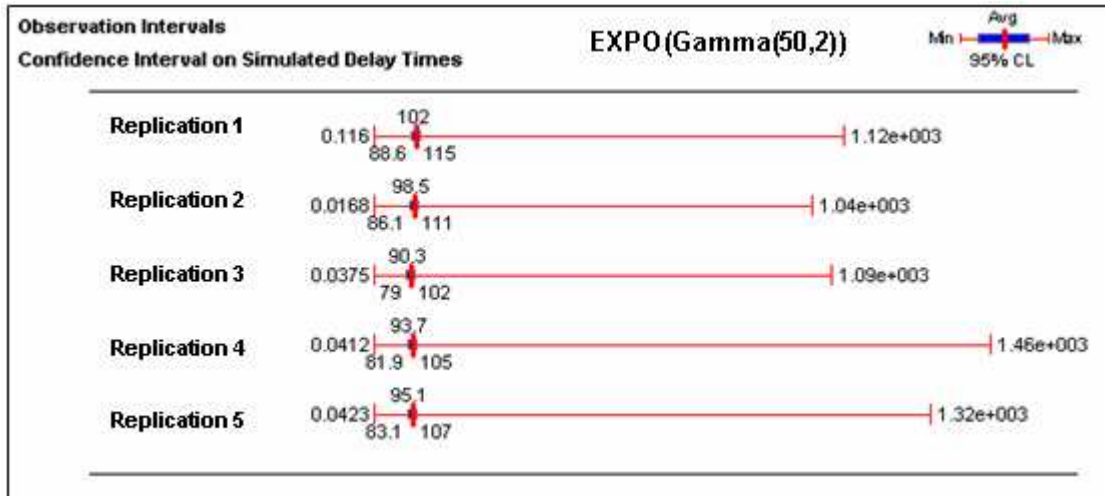


Figure 3-4 Confidence Intervals for the mean delay time for Level 3 injuries

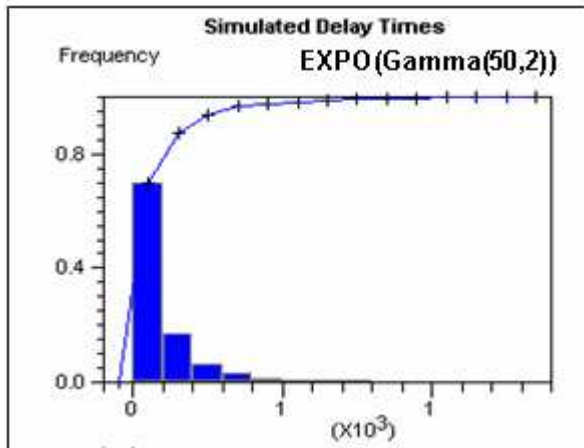


Figure 3-5 Delay times for Level 3 injuries

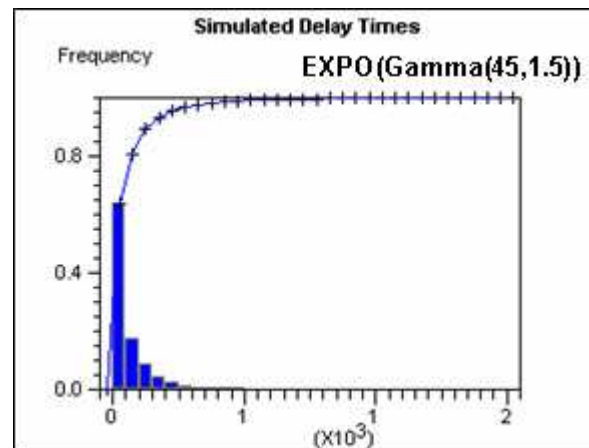


Figure 3-6 Delay times for Level 2 injuries

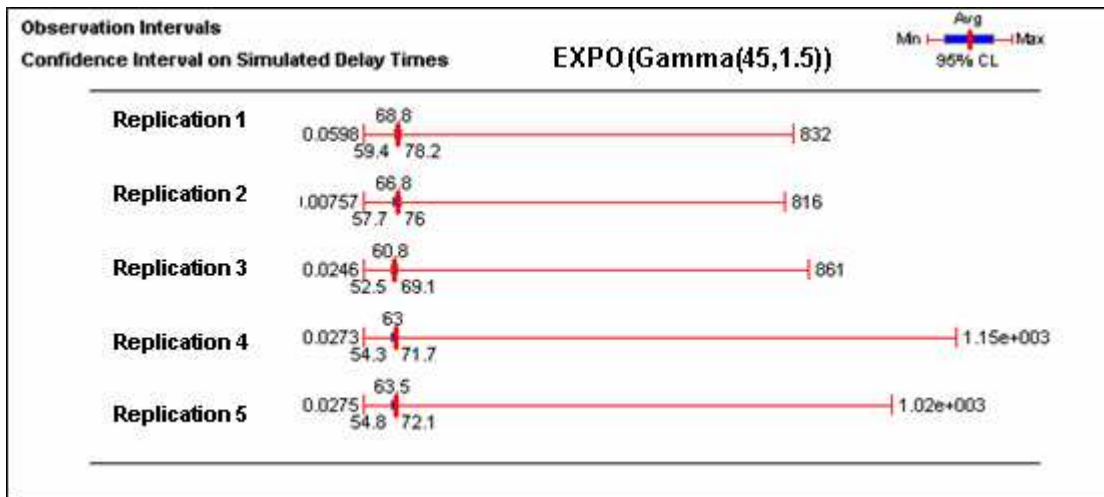


Figure 3-7 Confidence Intervals for the mean delay time for Level 2 Injuries

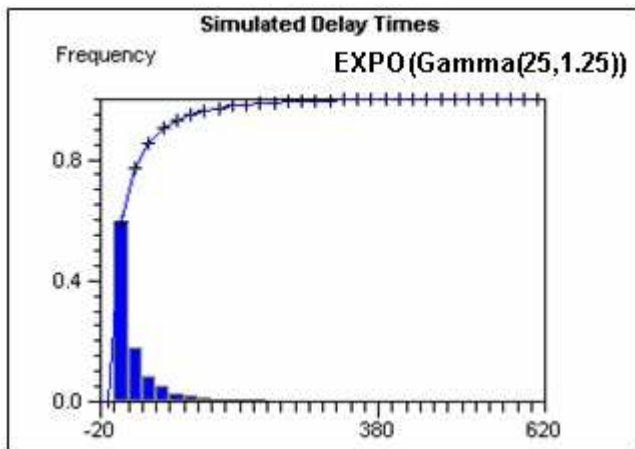
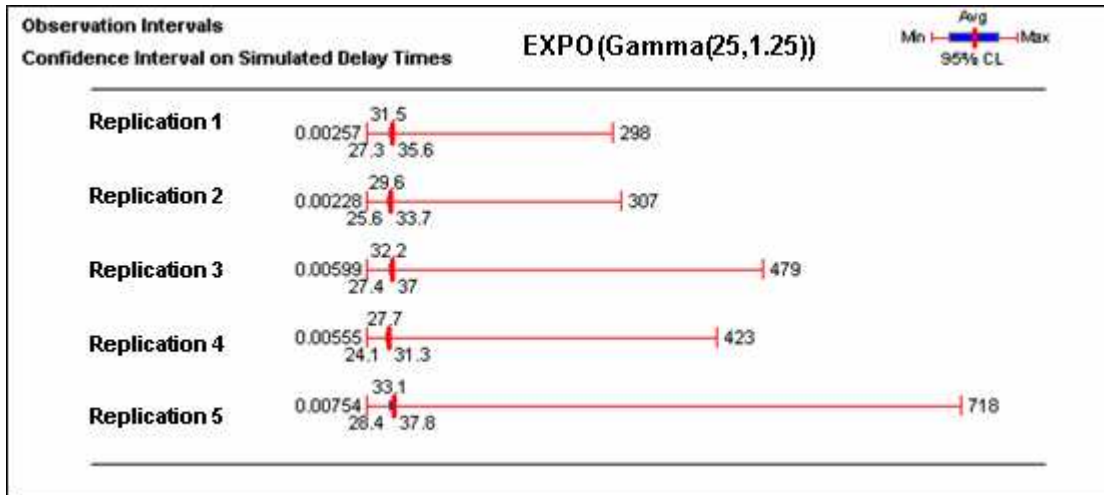


Figure 3-8 Histogram of delay times for Level 1 injuries



**Figure 3-9 Confidence Intervals for the mean delay time for Level 1 Injuries**

### 3.2.2.3 How to seek help

Once the victims are ready to seek help (they have exited the “Time to seek medical Attention” DELAY block) they must determine how they are going to seek help. There are many factors that may influence this decision, such as the availability of private transportation, the availability of ambulance transportation, the severity of their injuries, the distance to the hospital and if a triage center has been established, and if so if they know about it. First, it is determined if the victim is still alive. The DECIDE block, “Still Alive?” checks to see if the entity's attribute *Expiration Time* is still greater than TNOW. If it is, then the victim continues through the process, if it is not, then the victim has died and is counted in the Deaths RECORD block and then disposed of. Victims who are still alive are assigned an *Awareness* attribute. *Awareness* is equal to 0 if the victim is unaware of the field location (because it either does not exist or they have not been informed), and is equal to 1 if the victim is aware of the field location. In order to assign this, the variable *Percent Informed* is first set to:  $Information\ Dissemination\ Rate * Existence\ of\ Field\ Center$  where the information dissemination rate is a variable that is defined by the user before running the model (see section 3.2.1.5) and *Existence of Field Center* is a binary variable that is initially zero and is assigned to 1 by the model when the field station is established. *Awareness* is then assigned based on the expression:  $DISC(1-Percent\ Informed, 0, 1)$ . At this time, an attribute, *Help Sought*, is also assigned to the entity taking the value of TNOW and indicating at what time the victim began seeking help. The variable *Time of Last*

*Victim Seeking Help* is also set to TNOW to indicate how long it took for all patients to have sought help.

The entity then leaves the ASSIGN block and goes through a DECIDE block to separate the entities that have an *Awareness* value of 1 from those with a value of 0. Those with an *Awareness* value of 1 go through an ASSIGN block that assign distance attributes to each of the entities indicating the *Distance to Triage*, *Distance to Hospital 1*, *Distance to Hospital 2*, and *Distance to Hospital 3*. The attribute Shortest Distance to Help is then assigned to be the minimum of the distance values. The expression for each of these attributes is shown in Table 3-4.

**Table 3-2 Values assigned to attributes in Distances ASSIGN block**

<i>Attribute</i>	<i>Value Assigned</i>
Distance to Triage	Time(Location, Field Location)
Distance to Hospital 1	Time(Location, 4)
Distance to Hospital 2	Time(Location, 5)
Distance to Hospital 3	Time(Location, 6)
Shortest Distance to Help	Min(Distance to Triage, Distance to Hospital 1, Distance to Hospital 2, Distance to Hospital 3)

Once the distances for all of the possible destinations for the patient have been decided, the decision on whether they are going to go to the Triage Location must be determined. A DECIDE block with the expression: *Shortest distance to help==distance to triage* is used to determine if the Triage Station is the closest option for the victim. It is assumed that if the Triage Station is not the closest location for receiving medical attention, the victim will not choose to go to the Triage Station over going to a hospital emergency room. It is generally assumed by people that they will receive better medical care in an emergency room than in a field location, thus it would be uncommon for a victim to decide to go out of their way to go to a Field Location (see section 2.2.5). An attribute *Triage Desirability* is set up as a binary value, with “0” indicating that going to the Triage Station is an undesirable choice for the victim (either they are unaware of its presence or the distance to the triage location is greater than that of the distance to one of the hospitals) and “1” indicating that the Triage Station is a desirable option for the victim. Victims that evaluate “True” to the expression in the Go to Triage Location DECIDE block



(*Shortest Distance to Help*==*Distance to Triage*). Go to an ASSIGN block (ASSIGN 41) where the attribute *Triage Desirability* is set to 1.

Victims who had an Awareness equal to 0, go to the “Distances without Triage” ASSIGN block where the distance to each of the hospitals is evaluated and the *Shortest Distance to Help* is determined. This is done in the same way as the “Distances” ASSIGN block that is detailed above, except that the *Distance to Triage* is not evaluated or included in the calculation of *Shortest Distance to Help*.

After the distances to each of the hospitals have been evaluated as well as the desirability of going to the triage station, the availability of ambulances is evaluated before determining if the victim is going to seek help at the Triage station, by ambulance, or through private transportation to a hospital. The DECIDE block “Evaluate Availability of Ambulances” uses the expression:  $TAVG(Ambulance\ Wait\ Time) > 2 * Shortest\ Distance\ to\ Help / (1 - Percent\ Destruction(Location, 1))$  to determine if the amount of time that would be spent waiting for an ambulance is significantly longer than the amount of time that it would take for the patient to use private transportation or reach the triage station. This expression compares the average amount of time that is spent waiting for an ambulance to arrive to the amount of time to the amount of time that it would take to reach the closest form of help. If the average wait time for ambulances is less than twice the amount of time that it would take the patient to reach the closest form of help, then the desirability of ambulances will not be penalized and the attribute *Long Ambulance Queue* will be set to 0 (Assign 40). However, if the time that is spent waiting on an ambulance is more than twice the time of an alternative, then the attribute *Long Ambulance Queue* will be set equal to 5 (Assign 39) and will consequently decrease the probability that the victim will choose to use ambulance transportation. The value of 5 was selected because it will reduce the overall percentage of people who select ambulance transportation by 10 percentage points. If 20% would have chosen ambulance transportation, only 10% will now choose ambulance transportation. For many people, ambulance transportation may be the only option. This may be due to the lack of a personal vehicle or that their vehicle was destroyed by the tornado. The person may be injured beyond the point of being capable of transporting themselves and there may be no else available to transport them. Thus, even when ambulance wait times are large, there are still people who will have to select that option.

Once the *Long Ambulance Queue* value has been set, the entity goes through a BRANCH block to determine where it is going to seek help. The BRANCH block is 3-Way by chance. The first two percentages are given by the following expressions:

$$(Transportation Decision (1, Severity of Injury) + Long Ambulance Queue) * Triage Desirability$$

$$(Transportation Decision (2, Severity of Injury) + Long Ambulance Queue)$$

Where the first branch is sent to the triage station, the second branch chooses to use private transportation to reach the hospital, and the remaining people choose to wait for an ambulance.

*Transportation Decision* is a 3 x 3 matrix that gives the percentage of people that will make each choice if the ambulance wait time is not high and the triage station is a desirable option. The expression for the first branch will evaluate to zero if *Triage Desirability* is equal to zero. Long Ambulance Queue will be either 0 or 5, depending on the current average wait time for those being transported by ambulance. When it evaluates at 0, the percentage of people going to the Triage location and who choose private transportation is equal to the values in the *Transportation Decision* matrix (assuming *Triage Desirability* equals 1). If *Long Ambulance Queue* is equal to 5, an additional 5 percent of the people go to the triage location and an additional 5 percent choose private transportation, reducing the percent of people who will choose to wait for an ambulance. From this branch block, the victim will go to the “Triage Station”, “Private Transport to Hospital”, or “Load Ambulances” portion of the simulation. Each of these areas will be described in the subsequent sections.

#### 3.2.2.4 Triage Station

Victims that are going to the Triage station must first go through a DELAY block to represent the amount of time that it takes them to travel from their current location to the Triage station. The delay used is normally distributed with a mean of  $Distance\ to\ Triage * (1 - Percent\ Destruction(Location, 1) / 100)$  minutes and a variance of 2 minutes. A normal distribution was selected because it the commonly selected distribution used to describe travel times (Smeed and Jeffcoat 1971). The expression  $Distance\ to\ Triage * Max(1 - (Percent\ Destruction(Field\ Location, 1) / 100), 0.2)$  takes the time that it would take to reach the triage station under normal conditions, and multiplies it by a number between 0 and 1 that is dependent upon the *Percent Destruction* in the area. This is based upon the previous assumption that the travel time is dependent upon the *Percent Destruction*, see section 3.1.6

After the DELAY, the victim goes through an ASSIGN block where its station value, *M*, is set equal to *Field Location*. The value of *Field Location* represents the region in which the field location has been established. Another DELAY block is then used to represent the amount of time that the victim spends at the triage center prior to being stabilized to the point that they are ready to be transported as soon as an ambulance is available. The length of the delay is Uniform(5,30). It was assigned to this value based off of a conversation with Riley County EMS Lieutenant Sherry Reinhardt in which she expressed that it could take anywhere from 5 to 30 minutes to stabilize a patient depending on the number of patients that were in need of help, the severity and type of injuries, and the number of medical personnel available. She said that the “walking-wounded” and those with minor injuries will generally be transported to the hospital via buses or other non-ambulance modes. For this reason, in the model, none of the Level 1 injuries receive ambulance transportation after they visit the triage location and only half of the Level 2 victims receive ambulance transportation from the triage location to the hospital. All Level 3 injuries are sent to the “Load Ambulances” portion of the model because they will all require ambulance transportation.

#### ***3.2.2.5 Private Transport to Hospital***

*Victims* that choose private transportation to the hospital are simply counted using the *Private Transport to Hospital* counter, and then disposed from the system. They will not require ambulance assistance and thus considering their actions is not within the scope of this simulation.

#### ***3.2.2.6 Normal Call Volume***

The occurrence of a disaster does not release the EMS from its obligation to respond to “everyday” calls, see section 3.1.1. To simulate this, another CREATE block is used to create *victims*. These entities are created according the expression  $EXPO(\textit{Time Between Normal Calls})$ , where *Time Between Normal Calls* is a variable that must be initialized by the user before the simulation is run. The value of this variable should be assigned by using historic data and can be calculated by taking 1440 (the number of minutes in a day) and dividing it by the average number of calls received per day. This gives the average number of minutes between calls. Just like with the other *victims*, a *location*, an *M* value (station value), a *Severity of Injury*, and an

*Expiration Time* are assigned to each entity. The entities then go to the “Load Ambulances” section of the model.

### 3.2.2.7 Load Ambulances

As *victims* arrive at the “Load Ambulances” portion of the model, they first go through a RECORD block to record the Tally statistic *Ambulance Interarrival*. This is the time between subsequent arrivals at the block and represents the rate at which patients are requesting ambulance help. After recording this statistic, the *victims* are separated by location. During mass casualty events ambulances will transport multiple victims in the same ambulance. According to Riley County EMS Captain David Adams, this can be as many as four patients per ambulance. However, an ambulance would not pick up a patient from region 1 and a patient from region 2 and two patients from region 3, rather, an ambulance would go to a region and pick up as many of the victims at that region as possible and then transport them to the appropriate hospital. This is the reason for separating *victims* by region. The loading methodology is the same for all of the regions, thus it will only be explained for Region 1.

Each entity is assigned an attribute *TimeIn* which is equal to TNOW. This is the time that they began seeking ambulance help. This will be used later in the model to determine the *Ambulance Wait Time*, which is the amount of time that the *victim* waits for an ambulance to arrive.

*Location 1 Ambulance Key* is a resource that is used to ensure that the ambulances are loaded properly and the multiple entities are not going through the loading process at the same time. The resource capacity is 1 and the entity must seize this resource before it can go through the rest of the loading logic. The entity then goes to an ASSIGN block where it sets *Ambulance Severity of Injury* to: *Ambulance Severity of Injury* + *Severity of Injury*. The initial value for *Ambulance Severity of Injury* is 0. It then sets the variable *Number of Patients in Ambulance* to: *Number of Patients in Ambulance* + 1. The initial value of *Number of Patients in Ambulance* is 0.

A decide block is then used to determine if this is the first patient that will be loaded onto the ambulance, in which case the victim must request the ambulance, or if an ambulance is already on its way, then the victim can simply be added to the ambulance. The DECIDE block contains the expressions:

*Ambulance Loading* = = *Ambulance Number*

*Number of Patients in Ambulance* = = 1

*(Number of patients in ambulance <=4) && Ambulance Severity of Injury <8*

Else

The first expression determines if the current ambulance that is loading has already left for the hospital or not. Not all ambulances will be sent to the hospital full. Ambulances will arrive at the scene, pickup everyone that they can who is there, and then leave. If there are only 1 or 2 victims there, then they will leave with only 1 or two victims. If the first expression is evaluated as true, then the current ambulance has already left the region and thus the entity will have to request an ambulance.

If the second expression evaluates as true, then the previous ambulance is full (it may or may not have already left the region) and thus the victim will be the first entity into the next ambulance. Thus, the entity must request an ambulance.

If the third expression evaluates as true, then there is a partially full ambulance in the region. An ambulance is considered full when the number of patients reaches four or when the *Ambulance Severity of Injury* reaches 8 or higher. While ambulances can transport 4 victims, they will not have space or the personnel required to transport 4 level three injuries. When a partially full ambulance is available, the victim does not have to request an ambulance, rather they are assigned an attribute *Amb Num* equal to the variable *Ambulance Number*, release the *Location 1 Ambulance Key*, and then wait in the Pickup Queue for the partially full ambulance to pick them up.

Entities that must request an ambulance (Expression 1 or Expression 2 evaluates as true), go through the following logic. First, they go through an ASSIGN block and make the following assignments:

Variable: *Ambulance Number* = = *Ambulance Number* + 1

Attribute: *Amb Num* = = *Ambulance Number*

Variable: *Ambulance Severity of Injury* = = *Severity of Injury*

Variable: *Number of Patients in Ambulance* = = 1

*Ambulance Number* is a variable that increments by one each time a new ambulance is called. *Amb Num* records the value of the variable to the entity and serves like a serial number to tell the entity which ambulance-load it belongs to. As the first *victim* on the new ambulance load, it is up to this entity to reset the values of *Ambulance Severity of Injury* and *Number of Patients in Ambulance*.

Once all of the assignments have been made, the entity goes to an ALLOCATE block where it is allocated the next available ambulance. If multiple ambulances are available, the selection rule is Shortest Distance to Station or SDS. Once an ambulance has been allocated, the entity releases the *Location 1 Ambulance Key* so that another entity can begin going through the loading process. A MOVE block then moves the allocated ambulance to the location of the victim, which for Location 1 is Station 1.

Once the ambulance arrives at station, the entity then re-seizes the Location 1 Ambulance Key. It assigns the variable *Ambulance Loading* to its attribute *Amb Num*. A SEARCH block then searches the *Pickup Queue* for entities with the same *Amb Num*. The Pickup Queue has the queuing rule of First-in-First-Out, thus the values of *Amb Num* will be in order from smallest to largest. Thus the expression,  $Amb\ Num > Ambulance\ Loading$  identifies the first entity that belongs to a different ambulance and sets *J* equal to that value. After searching the queue the entity then goes through a PICKUP Block. If the search did not return any entity in which the expression was met, then all entities in the queue belong to the same ambulance. Thus, the number of entities picked up is  $NQ(Pickup\ Queue)$ , which is the number of entities in the *Pickup Queue*.  $NQ(X)$  is the Arena notation for the number of entities in queue *X*. If a value is returned for *J*, then the number picked up is  $J-1$ . The *Location 1 Ambulance Key* is then released. The entity is now actually a group of entities and it goes to the “Ambulance Transportation” section of the model.

### **3.2.2.8 Ambulance Transportation**

First the amount of time that was spent waiting on an ambulance to arrive is calculated by the Tally *Ambulance Wait Time*, which evaluates the time interval of TimeIn ( $TNOW - TimeIn = Ambulance\ Wait\ Time$ ).

The amount of time that the ambulance spends on the scene is then considered by the Time on Scene DELAY block. The time on scene delay was determined using the conclusions of the study done by Morrissey and Ohsfeldt (1996). An overview of this study is given in the Literature Review in Chapter 2, section 2.4.1. The statistics for trauma patients who were found alive on the scene were used, because it is assumed that those who are found dead will not be treated or transported until those who are still alive and are in need of medical attention have been helped. The study only gave mean, standard deviation and 50<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> percentile data, but did not give the distribution that would fit the data. It was found that a Gamma

distribution with a shape parameter of 3.1 and a scale parameter of 0.2222 would produce similar statistics. The statistics produced by this distribution can be seen and compared to the actual Morrisey and Ohsfeldt statistics in Table 3.5.

**Table 3-3 Comparison of Gamma distribution to statistics for trauma time on scene**

	n	Mean	St.Dev	Mean by Percentile		
				50th	75th	90th
<b>Actual (Morrisey and Ohsfeldt)</b>	2416	13.9	7.9	12	18	23
<b>Gamma(3.1, 4.5)</b>	10000	13.948	7.92	12.48	18.18	24.57
<b>Difference (Gamma-Actual)</b>		0.048	0.02	0.48	0.18	1.57

The expression:  $\text{Gamma}(.222222, 3.1) * \text{NG}$  is used for the delay, with NG being the number of victims in the group. After the delay, the entities are separated out by the severity of their injuries to determine which hospital the ambulance will take them to. If there is a Level 3 injury, then the victim will be taken to a Level 1 Trauma Center. Under the assumptions of the model, Hospital 1 is the closest Level 1 Trauma Center. Thus, all ambulances containing a Level 3 injury will be routed to Hospital 1.

If the entity has Level 1 injuries, then their injuries are minor and do not require special treatment, thus the patient will go to the hospital that is the shortest distance away. Level 2 injuries may require more sophisticated care; however they do not necessarily need a Level 1 Trauma Center. Some people with Level 2 injuries may decide to go to the closest hospital, while others may decide to go a little further to a better hospital. For this model, it is assumed that half of the people with Level 2 injuries will make their decision based on the closest hospital while the other half will seek a larger hospital (Level 1 or 2 Trauma centers).

This is done by evaluating the *Trauma Levels* for each of the hospitals. *Trauma Levels* is an  $h \times 1$  matrix that gives the trauma level, 1-3, for each of the hospitals. If the trauma level is equal to three, then the victim will not want to be routed to that hospital. The *Distance to Hospital #* attribute is thus set to a very large number, making it undesirable. Once all of the hospitals have been evaluated, the attribute *Shortest Distance to Help* is set to:  $\text{Min}(\text{Distance to Hospital 1}, \text{Distance to Hospital 2}, \text{Distance to Hospital 3})$ . A DECIDE block then compares each of the *Distance to Hospital #* attributes to the *Shortest Distance to Help* to determine which of the hospitals the *victim* will be routed to. The attribute *Hospital Selected* is then set to the appropriate station number and the entity goes to the TRANSPORT block. An ambulance transporter is used with a destination of *Hospital Selected*. The velocity of the transporter is set

to:  $\text{Max}(1-(\text{Percent Destruction}(\text{Location},1)/100),0.2)$ . This expression takes into consideration that increasing percent destructions will result in longer travel times due to debris in the roads, see assumption 6, Section 3.1.6. It puts a lower limit of the velocity at 0.2, which would make the travel time five times the normal travel time. This is done to prevent the velocity from reaching zero if the percent destruction is set at 100%.

From the TRANSPORT block the entities are routed to the appropriate hospital station. A Separate block then duplicates the entity, sending the duplicate through a series of logic that represent the “ambulance driver” and take control of the ambulance. The originals then go through a second separate block and are split into the original entities, with each entity retaining its original values. A DECIDE block evaluates the value of *Expiration Time* to determine if the victim arrived at the hospital in time. If TNOW is greater than *Expiration Time*, the victim is considered dead and is counted and disposed of. If TNOW is less than *Expiration Time*, then arrival times are collected and then the patient is disposed.

Meanwhile, the entity that has become the “ambulance driver” goes through a DELAY for decontaminating and restocking the ambulance. According to Riley County EMS Captain Dave Haefke the amount of time for this will range from 5 to 30 minutes depending on the amount of decontamination that needs to occur. He said the most likely value would be about 10 minutes. Thus, a Triangular(5,10,30) was used to simulate this delay time.

The entity then enters a MOVE block and moves the ambulance back to the field location. This is done under the assumption that many of the communication lines, whether phones or radios, are not useable. Thus, a regular dispatching pattern is not being used, rather when an ambulance is available it returns to the field location and is then dispatched from there. Section 2.2.2 talks about the breakdown of communication that can occur in disasters. Once the ambulance has been moved to the field location, it is freed. At this point the *Total Ambulance Time Tally* is recorded and then the entity is disposed.

### **3.2.2.9 EMS Director Decisions**

While victim entities are going through the section of the model described above, *Local EMS official* entities are going through a separate portion of the model evaluating the situation and making decisions that change the values of global variables and the status of transporters.

A CREATE block creates a single Local EMS official entity at time equals *Officials Alerted*. *Officials Alerted* is a user specified time that indicates at what point the EMS officials



realize that there is a problem. This could be equal to zero if the EMS officials know that the tornado is coming, it could be longer if the first indication that they receive is when patients begin arriving at the hospital. The default value of *Officials Alerted* is zero. With the weather forecasting tools that exist today, emergency officials are often aware of and monitoring the possibility of a tornado before it actually occurs.

Once the *Official is Alerted*, there is a delay for the official to create a plan. This is a very short delay, because it is assumed that a disaster response plan already exists and the only real decision is at what level the plan should be enacted. Riley County EMS Captain Dave Haefke commented that the initial truck and a supervisor will be dispatched within one minute of notification of the disaster and the disaster plan will be activated at Level 1; however, the rest of the plan will not be activated until information is received from those at the scene of the disaster. This could be the EMS personnel that are dispatched when receiving the call or it could be reports from police or fire crews that reach the scene first. To fully activate the plan at the appropriate level, it could take officials up to 30 minutes, not to mention the time that it takes to travel to the scene of the disaster once the plan has been enacted. Based on the information from Haefke, the delay time was set using a UNIFORM(1,30) distribution.

An ASSIGN block is then used to initialize the number of ambulances available and make the decision of in which region to locate the Triage station. An assumption of the model is that only one triage center will be created. It will be created in the area that sustained the most injuries. Thus the variable *Max Injuries in Region* is set to:  $\text{Max}(\text{NC}(\text{Region 1 Number Injured}), \text{NC}(\text{Region 2 Number Injured}), \text{NC}(\text{Region 3 Number Injured}))$ . In Arena code, NC(X) is the value of counter X. A BRANCH block is then used to determine which of the regions has the maximum number of injuries. The variable *Field Location* is then assigned to the appropriate region value.

The entity then goes through a SEPARATE block to allow it to complete multiple functions simultaneously. *OD 1 Total Ambulances* + *OD 2 Total Ambulances* duplicates of the entity are made and are sent through the “Set up Field Station” portion of the model. The original goes to the “Release Out of District Ambulances” portion of the model.

### **3.2.2.10 Request Out of District Ambulances**

The expression to determine if more ambulances are needed is:

$$\frac{1}{2} * \frac{\text{Max}(\text{TAVG}(\text{TotalAmbulanceTime}), 30)}{\text{TAVG}(\text{TimeBetweenHelpSought})} > \text{MT}(\text{Ambulance}) + \sum_{\# = 1}^8 \text{OD}\# \text{InrouteDisaster}$$

The numerator is the average of the Tally statistic *Total Ambulance Time*, which is the average amount of time that it takes an ambulance to go from picking a patient up to being freed and available to be dispatched to another patient. This can be thought of as the total time for one ambulance trip. At the beginning of the simulation, no ambulance trips will have been made and the tally value would evaluate at zero. This is why the Max function is used. A value of 30 minutes is a very conservative estimate for the total amount of one ambulance trip. The denominator is the average of the tally statistic *Time Between Help Sought* which is the inter-arrival time of patients at the “Load Ambulances” portion of the model. The left side of the expression can be seen as the amount of time that it takes for one trip to the hospital divided by the rate at which victims are arriving, thus it will give the approximate number of ambulances that are needed to serve all of the victims. It is multiplied by ½ under the assumption that ambulances will be transporting multiple patients at a time. This allows for the average ambulance to be transporting 2 victims. If this value is greater than the number of activated ambulances, *MT(Ambulance)* plus the number of ambulances that are in-route to the disaster then more ambulances will be requested.

If the expression evaluates as false, the entity is sent to a delay block, waits 30 minutes, and then reevaluates the need for the transporter. If the expression evaluates as true, then the entity seizes the *Ambulance Dispatch Key* and then goes through a branch block to determine which district to request the ambulance from. The ambulance is requested from the region with the max percentage available. If there is a tie (say both are at 100%), then it is requested from the closest region first, based on the assumption that out of district regions are numbered in order of closest to furthest from the local region. The entity is sent to the section of the model for the appropriate district.

### 3.2.2.11 Out of District #

When arriving at the appropriate “Out of District #” section of the model, the entity amends the values of the variables: *OD # requested*, *OD # Available*, *OD # Percent Coverage* and the attribute *Ambulance to Release*, where # is the number of the district. The new values of these variables are:

<i>Variable/Attribute</i>	<i>Value Assigned</i>
<i>OD # Requested</i>	<i>OD # Requested + 1</i>
<i>OD # Available</i>	<i>OD # Available - 1</i>
<i>Ambulance to Release</i>	<i>OD # Ambulances + OD # Requested</i>
<i>OD # Percent Coverage</i>	<i>OD 1 Ambulances Available/OD 1 Total Ambulances</i>

The Ambulance Dispatch Key is then released so that other ambulances can be requested. A DELAY block then delays the entity for an amount of time represented by the distribution: Normal(*Times for OD Ambulances(Field Location, #)*, 2). *Times for OD Ambulances* is a matrix of travel times that must be input into the model, see section 3.2.1.3. A normal distribution is used because this is a common distribution to use for travel times. A standard deviation of 2 allows for variation depending on the condition of the roads, traffic, etc.

An ACTIVATE block is then used to change the status of the ambulance transporter from inactive to active. The unit number of the ambulance is *Ambulance to Release*, which is an attribute that was assigned to the entity when the decision to release an ambulance was made. Once the ambulance is activated, the entity is disposed.

### **3.2.2.11 Set up Field Station**

The original of the *Local EMS Director* entity was sent to this section of the model. As soon as the field location is established, emergency personnel such as police and relief workers can begin telling the public where the triage station will be at. An ASSIGN block is used to change the variable *Existence of Field Center* to 1 and the variable *Creation of Field Center* to TNOW.

A DELAY block delays the entity for the amount of time that it will take for emergency personnel to reach the chosen site for the triage or field station. The value of this delay is normally distributed with a mean of  $Time(Ambulance Station, Field Location) * \text{Max}(1 - (Percent Destruction(Field Location, 1)/100), 0.2)$  where *Ambulance Station* is a variable that is input by the user before the model is run and *Field Location* is a variable that was determined by the model in the “EMS Director Decisions” section of the model. As indicated before:  $\text{Max}(1 - (Percent Destruction(Field Location, 1)/100), 0.2)$  is the velocity at which ambulances can travel due to the destruction and blockage of roadways. The standard deviation is set to 2 to allow for

variation depending on the condition of the roads, traffic, etc. Once the emergency crews arrive at the field location area, then the triage center still has to be set up. According to Riley County EMS Captain Adams, this will generally take approximately 30 minutes. In the delay block, the delay is represented by the distribution Normal(30, 2). At this point the field location is up and running, so the variable *Field Station Operating* is set to 1 and the *Time Field Station Operating* is set to TNOW. The entity then goes to the “Release Out of District Ambulances” section of the model.

### **3.2.2.12 Release Out of District Ambulances**

A single Local EMS official entity will enter this section of the model and go to a decide block that contains the expression:  $(NT(ambulance)/MT(ambulance)) < Release\ Rule$ . Where in Arena code, NT(X) is the number of transporters of type X that are currently busy and MT(X) are the number of transporters of type X that are currently available. This expression is evaluating if the utilization of the ambulances is less than a specified percentage contained in the variable *Release Rule*. *Release Rule* is determined by the user before the model is run. If the expression is false, then the entity is delayed for 10 minutes and then goes back through the same BRANCH block. Once this value is evaluated as true, then the entity goes to a delay block, is delayed for 10 minutes and then is re-evaluated for the same condition at a second delay block. This is to prevent ambulances from being prematurely released at the first small lull in the demand. If the expression evaluates as false at second BRANCH block, then it returns to the first BRANCH block. If the expression still evaluates as true at the second BRANCH block, then the entity seizes the *Release Ambulance Key* and begins the process of releasing an ambulance.

First, an ASSIGN block updates the values of the OD # Percent Released variables to be equal to:  $(OD\ \# \ Ambulances\ Available + OD\ \# \ Inroute\ Home) / OD\ \# \ Total\ Ambulances$ . This is the number of ambulances that are currently available and the number of those currently in-route to returning to their home district divided by the total number of ambulances for this district. The expression:  $Min(OD\ 1\ Percent\ Released, OD\ 2\ Percent\ Released)$  is then used to evaluate the *Min Percent Released*.

A BRANCH block then determines if all of the ambulances have already been released (*Min Percent Released* = =1) or which district’s ambulance should be released *Min Percent Released* = = *OD # Percent Released*. If all of the ambulances have been released, then the variable *All Ambulances Released* is set to 1 and the entity is disposed of. Otherwise, the entity is

routed through the appropriate set of blocks based on the district from which the ambulance is being released. These blocks are similar for each district, just changing the value of # in the variables. An ASSIGN block updates the *OD # Ambulances Released* and *OD 2 Inroute Home* variables and the *Send Home Ambulance* attribute as follows:

<i>Variable/Attribute</i>	<i>Value Assigned</i>
<i>OD # Ambulances Released</i>	<i>OD # Released + 1</i>
<i>OD # Inroute Home</i>	<i>OD # Inroute Home + 1</i>
<i>Send Home Ambulance</i>	<i>OD # Ambulances + OD # Ambulances Released</i>

The entity then goes through a HALT block and changes the status of ambulance number *Send Home Ambulance* to inactive. The *Release Ambulance Key* is then released so that other ambulances can be released. A SEPARATE block sends the original entity back through the system to see if any other ambulances need to be released. The duplicate goes through a DELAY block that simulates the time it takes for the ambulance to return to its home area from the disaster area. Its delay time is  $\text{Normal}(\text{Times for OD Ambulances}(\text{Field Location, \#}), 2)$ . This is the same delay time that was used for the ambulance to reach the disaster area when it was dispatched, see section 3.2.2.11. After this delay, another ASSIGN block is used to update the value of the variables that control the out of district ambulances. The values were set as follows:

<i>Variable/Attribute</i>	<i>Value Assigned</i>
<i>OD # Ambulances Available</i>	<i>OD # Ambulances Available + 1</i>
<i>OD # Requested</i>	<i>OD # Requested - 1</i>
<i>OD # Percent Coverage</i>	<i>OD # Ambulances Available/OD # Total Ambulances</i>
<i>OD # Inroute Home</i>	<i>OD # Inroute Home - 1</i>

After updating these variables, the entity is disposed of.

### 3.3 Running the Simulation

After initializing the simulation by inputting the information described in section 3.2.1, the simulation can be run. The run time of the simulation is negligible (5 replications took 0.7

minutes). During the simulations statistics on the values of each of the variables can be collected; however, the ones that have been chosen to be recorded in the output are the *OD # Percent Coverage*, *OD # Below 50%*, *Active Ambulances*, and *Arrival Time* variables.

Tallies are used to record the Total Ambulance Time, Ambulance Wait Time, and Time to Arrival at Hospital. The Total Ambulance Time is the amount of time that it takes for one complete ambulance trip, from the time that they are allocated to a victim to when they are released to assist another victim. The Ambulance Wait Time is the amount of time that passes between when a victim begins seeking help and when an ambulance arrives to transport them. Time to Arrival at Hospital is the amount of time from when a victim begins seeking help to when they arrive at the hospital.

Counters are used to record the number of each type of injury, the number of injuries that occur in each region, and the number of people who die. The number of ambulance trips to the hospital is also recorded through a counter.

Other statistics could be collected while running the simulation; however, these are the statistics that were seen as necessary for validating the model and testing decision rules. Chapter 4 explains the model validation processes, and in Chapter 5 the statistics are used to evaluate decision rules.

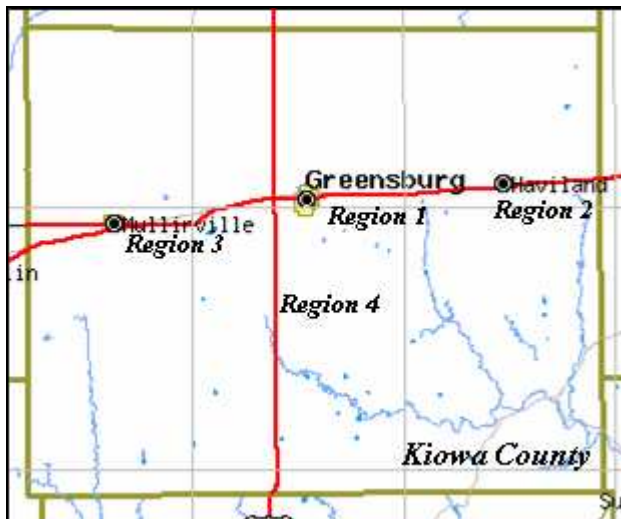
# CHAPTER 4 - Results and Model Validation

## 4.1 System Setup

The tornado that hit Greensburg, Kansas on May 4<sup>th</sup>, 2007 was used as a reference to test out the system. Greensburg is a small, rural town in Kiowa County. The input variables were all set based upon Kiowa County.

### 4.1.1 Regions, Distances and Population

The county was divided into four regions, the first three representing each of the three small towns in the county: Greensburg, Haviland, and Mullinville. The third region represents all of the people living outside of any of these three towns. Figure 4-1 shows a map of Kiowa County and each of regions assigned for the model. Distances for Region 4 were calculated from the geographical center of the county.



Region Population Matrix	
Region	Population
Greensburg	1452
Haviland	589
Mullinville	266
Other	677

Figure 4-1 Map of Kiowa County

Table 4-1 Value of *Region Population* Variable

The values for the *Time* variable were found by using Google Maps and obtaining the driving directions from the center of each of the regions to the appropriate point (center of

another region or hospital). The approximated driving time was then used as the time-distance value. Table 4-2 shows the values that were used for the *Time* matrix.

**Table 4-2 Value of *Time* variable**

Time Matrix							
	Greensburg	Haviland	Mullinville	Other	Wichita Via Christi	Pratt Regional Med Center	Western Plains Medical Center
Greensburg	4	11	11	10	120	33	55
Haviland	11	2	23	21	112	25	67
Mullinville	11	23	1	20	133	46	44
Other	10	21	20	23	130	44	64

Many sources reported the percent destruction for Greensburg at 95%. No reports were found for the percent destruction that occurred in the rest of the county. The tornado was on the ground for 22 miles, sweeping across a large portion of Kiowa county (Ablah 2007). Arbitrary values of 30 percent destruction were selected for both Haviland and Mullinville. Since the rest of the county is such a large area, only 20 percent was selected for this area. Such small percentages are unlikely to generate many if any injuries in the simulation, but they do provide the possibility of an injury occurring in these areas. Table 4-3 shows the value of the *Percent Destruction* variable.

**Table 4-3 Value of Percent Destruction Variable**

Percent Destruction Matrix	
Region	Destruction
Greensburg	95
Haviland	30
Mullinville	30
Other	20

There are 5 hospitals that are within a short travel of Greensburg or are the nearest Level 1 trauma center; however, only three hospitals were considered for the simulation. The assumption that the first hospital is the closest level one trauma center was fulfilled by using Wichita’s Via Christi hospital as the first hospital in the simulation. A majority of the victims of the tornado were sent to Pratt Regional Medical Center, which is approximately 30 minutes east of Greensburg. It is a level 2 trauma center and is much larger than the rural community hospitals that are the same or a greater distance in other directions. Finally, Western Plains Medical Center which is located in Dodge City was used for the third hospital. It too is a Level 2 trauma center.



From Greensburg, it is farther than Pratt Regional Medical Center; however, from Mullinville it is slightly closer. Table 4-4 gives a summary of the hospitals used and their trauma levels.

**Table 4-4 Value of Trauma Levels Variable**

Trauma Levels	
<i>Hospital</i>	<i>Level</i>
Wichita Via Christi	1
Pratt Regional Med Center	2
Western Plains Medical Center	2

*Willingness* was arbitrarily set to 0.7, indicating that approximately 70% of those who were not injured will assist in search and rescue. The impact of varying this variable was not evaluated; however, its affect would be similar to that of increasing the volunteer injury rate. Together, the two variables determine how many people will be injured during the search and rescue phase.

#### **4.1.2 Normal Calls**

*Time Between Normal Calls* is 1440 minutes, this represents one normal call per day. The historical data for Kiowa County was not available, and this estimate is likely to be more calls per day than what is typical of a county of this size. According to general rules of thumbs, the number of emergency transports completed by an ambulance district can be expected to be approximately 3.5% of the population per year (Cadigan 1989). Kiowa County’s population of approximately 3000 people result in an expected call volume of one every 3.5 days. With an average of one call per simulation run, the normal calls are unlikely to have a significant impact on the simulation; however, the fact that ambulances must still respond to their regular demands could not be overlooked. Table 4-5 shows the value that was used for the variable Normal Call Severity. Once again, historical data was not available and the numbers were selected arbitrarily. An effort to determine highly accurate values for this variable was not made since the number of calls going through the system during the twenty-four hour simulation (an average of one) was known to be small and the affect of the value of this variable would be very small.

The *Location of the Normal Call* has the possibility of having a larger impact on the system. If the normal call occurs in an area where there are no other victims, an ambulance will have to go after the single patient, whereas if it occurs in the disaster area where there are many

victims and ambulance would be shared with others. The values for the location of normal calls were calculated based upon the population of each region, with the assumption being made that all people are equally likely to call for an ambulance. These values are shown in Table 4-6.

**Table 4-5 Value of Normal Call Severity**

<b>Normal Call Severity</b>	
<i>Level</i>	<i>Value</i>
1	0.25
2	0.5
3	0.25

**Table 4-6 Value of Location Normal Calls**

<b>Location Normal Calls</b>	
<i>Region</i>	<i>Percent</i>
Greensburg	0.49
Haviland	0.2
Mullinville	0.09
Other	0.02

### **4.1.3 Ambulance Transporters**

Kiowa is a part of Kansas EMS Region III. Disaster preparedness is something that this region has taken seriously. They have formed what is known as MERGe, Major Emergency Response Group. The group facilitates communication between ambulance districts and provides combined training and response plans. When a disaster occurs within the coverage area of one of the counties, it is the other MERGe ambulances that will lend their services. Figure 4-2 shows all of the ambulance districts that participate in MERGe. Table 4-7 gives a list of each of the ambulance districts and the number of ambulances that they staff. Their distance in minutes from Greensburg is also given.



**Figure 4-2 Locations of Ambulance Districts Participating in MERGe**

**Table 4-7 MERGe Ambulance Districts (Region III EMS)**

<b>MERGe Ambulances</b>				
<b>Ambulance District</b>	<b>Ambulances Staffed</b>	<b>Minutes to Greensburg</b>	<b>Weighted Minutes</b>	<b>Group</b>
Pratt County EMS	2	32	64	1
Comanche County EMS	2	52	104	2
Edwards County Ambulance	1	46	46	3
Larned EMS	1	69	69	3
Burdett EMS	1	74	74	3
Central Rush County EMS	1	85	85	3
Rush County Ambulance Dist. #1	1	85	85	3
Stafford County EMS	3	61	183	4
Great Bend Fire Dept.	2	86	172	4
Ellinwood EMS	1	96	96	4
Hoisington EMS	2	101	202	4
Claffin Fire & EMS	2	108	216	4
Rice County EMS	2	121	242	4
Kingman EMS	1	69	69	5
Pretty Prairie EMS	1	92	92	5
Reno County EMS	5	92	460	5
Sedgwick County EMS	15	110	1650	6
Haven EMS	1	115	115	5
Mt. Hope Community Ambulance	1	119	119	5
Norwich EMS	1	118	118	7
Clearwater EMS	2	122	244	7
Argonia EMS	1	137	137	7
Mulvane EMS	1	138	138	7
Belle Plaine EMS	1	142	142	7
Halstead EMS	1	137	137	8
Newton Fire/EMS	4	144	576	8
Hesston EMS	2	147	294	8
Butler County EMS	3	148	444	8
McPherson EMS	2	151	302	TF
Moundridge EMS	1	154	154	TF
Sumner County Hospital District #1	1	158	158	TF
Canton Ambulance Service	1	161	161	TF
Lindsborg EMS	1	164	164	TF
Florence Ambulance Service	1	166	166	TF
Marion County EMS	4	178	712	TF
Arkansas City Fire/EMS	3	184	552	TF
Greenwood County EMS	1	199	199	TF
Fredonia EMS	2	228	456	TF
Iola Fire/Allen County EMS	2	235	470	TF
Sedan Area EMS	1	235	235	TF
Neodesha EMS	2	242	484	TF
Independence EMS	1	256	256	TF
Cherryvale Fire/EMS	1	263	263	TF
Neosho Memorial Regional Medical	3	274	822	TF
Erie Emergency Care Group	1	278	278	TF
Coffeyville Regional Medical	3	281	843	TF
Labette County Medical Center	4	286	1144	TF
Crawford County EMS	3	301	903	TF
Cherokee County Ambulance	2	317	634	TF

Not all of the ambulances in MERGe are within a reasonable distance of Greensburg. All ambulances that were greater than 150 minutes (2.5 hours) away were considered too far to provide assistance. This left 61 ambulances within a “reasonable” distance to the disaster area. These ambulances were broken up into 8 groups based upon their location. It would be too tedious to input all of the districts individually into the model. The distance for each of the groups was considered to be the weighted average of the distances to each of the individual districts within the group. If a district staffs two ambulances, its distance would be considered twice while the distance to a district that only staffs one ambulance is only considered once. Figure 4-3 shows a map of the groups. The districts marked by the markers that do not have a dot in the center are not considered by the simulation because their distance is too far (greater than 2.5 hours).



**Figure 4-3 Grouping of Ambulance Districts for Simulation**

Using this information, the variables for the simulation can be set. Tables 4-8 and 4-10 contain the values that would be put into the *OD Total Ambulances*, *Times for OD Ambulances*, and *OD # Ambulances* variables.

**Table 4-8 Values for Out of District Ambulances**

<b>Out of District Ambulances</b>			
<b>Group</b>	<b>Total Ambulances Staffed</b>	<b>Average Minutes</b>	<b>Weighted Average Minutes</b>
1	2	32	32
2	2	52	52
3	5	71.8	72
4	12	95.5	93
5	9	97.4	95
6	15	110	110
7	6	131.4	145
8	10	144	156
<b>Total</b>	61		

**Table 4-9 Ambulances by simulation district**

<b>Ambulances</b>					
<b>Ambulance</b>	<b>District</b>	<b>Ambulance</b>	<b>District</b>	<b>Ambulance</b>	<b>District</b>
1	Local	22	4	43	6
2	Local	23	4	44	6
3	1	24	5	45	6
4	1	25	5	46	6
5	2	26	5	47	6
6	2	27	5	48	7
7	3	28	5	49	7
8	3	29	5	50	7
9	3	30	5	51	7
10	3	31	5	52	7
11	3	32	5	53	7
12	4	33	6	54	8
13	4	34	6	55	8
14	4	35	6	56	8
15	4	36	6	57	8
16	4	37	6	58	8
17	4	38	6	59	8
18	4	39	6	60	8
19	4	40	6	61	8
20	4	41	6	62	8
21	4	42	6	63	8

**Table 4-10 OD # Ambulances variables**

<b>OD # Ambulances Value</b>	
<b>Variable</b>	<b>Value</b>
OD 1 Ambulances	2
OD 2 Ambulances	4
OD 3 Ambulances	6
OD 4 Ambulances	11
OD 5 Ambulances	23
OD 6 Ambulances	32
OD 7 Ambulances	47
OD 8 Ambulances	53

## 4.2 Sensitivity Analysis

A 3<sup>4</sup> Experimental Design was used to perform a sensitivity analysis on the variables: *Volunteer Injury Rate*, *Injury Level*, *Information Dissemination Rate*, and *Transportation Decision*. This allows us to see how the value of each of these variables affects the system. Each of these variables was run at three different levels. This allows for the possibility that their effect on the response variables is not linear. The values of these levels are shown in Figure 4-4. The statistics: Total Ambulance Time, Ambulance Wait Time and Time to arrival at hospital were used as responses. Total Ambulance Time is the amount of time that it takes one ambulance to make one complete hospital run. This is the time from when the ambulance is allocated to a patient to when it is released and available to be allocated to another patient. The Ambulance Wait Time is the amount of time that a victim spends waiting for an ambulance once they have made the decision that they are going to seek ambulance transportation. Time to arrival at hospital is the amount of time that it takes for the patient from the time they begin seeking help to when they are at the hospital. For analysis, the average of each of these statistics is used.

<b>DOE Factors</b>					
<b>Variable</b>			<b>Variable</b>		
	<b>Level</b>	<b>Value</b>		<b>Level</b>	<b>Value</b>
<b>A:</b> Volunteer Injury Rate	1	0.25	<b>C:</b> Information Dissemination Rate	1	0.3
	2	1		2	0.6
	3	4		3	0.9
<b>B:</b> Injury Severity	1	0.7	<b>D:</b> Transportation Decision	1	60 45 20
		0.2			30 35 50
		0.1			10 20 30
	2	0.5		2	50 40 10
		0.3			30 30 40
		0.2			20 30 50
	3	0.3		3	60 40 10
		0.4			10 20 30
		0.3			30 40 60

**Figure 4-4 DOE Factors and their levels**

### 4.2.1 Total Ambulance Time

The ANOVA table produced from the DOE analysis in MiniTab is shown in Figure 4-5. At an alpha level of 0.05, the factors A, D, AB and BC are found to have a significant contribution towards the variation in the Total Ambulance Time. That is the *Volunteer Injury*

Rate, Transportation Decision and the interaction between Injury Severity and Volunteer Injury rate and the interaction between the Injury Severity and the Information Dissemination Rate. The residual values are relatively high and widespread, as can be seen in the Histogram of the Residuals in Figure 4-6.

ANOVA Table: Total Ambulance Time							
A=Volunteer Injury Rate B=Injury Severity							
C=Information Dissemination Rate D=Transportation Decision							
Source	DF	Seq SS	Adj SS	Adj MS	F	P	Significant?
A	2	94527.4	94527.4	47263.7	299.55	0.000	*
B	2	222.1	222.1	111.0	0.70	0.509	
C	2	289.7	289.7	144.8	0.92	0.419	
D	2	8620.4	8620.4	4310.2	27.32	0.000	*
A*B	4	5550.6	5550.6	1387.6	8.79	0.001	*
A*C	4	207.3	207.3	51.8	0.33	0.855	
A*D	4	1095.9	1095.9	274.0	1.74	0.191	
B*C	4	1987.4	1987.4	496.9	3.15	0.043	*
B*D	4	578.9	578.9	144.7	0.92	0.478	
C*D	4	1047.7	1047.7	261.9	1.66	0.208	
A*B*C	8	2550.7	2550.7	318.8	2.02	0.110	
A*B*D	8	2275.0	2275.0	284.4	1.80	0.150	
A*C*D	8	1114.9	1114.9	139.4	0.88	0.551	
B*C*D	8	1522.8	1522.8	190.3	1.21	0.355	
Error	16	2524.5	2524.5	157.8			
Total	80	124115.3					

Unusual Observations for Total Ambulance Time					
Obs	Total Am	Fit	SE Fit	Residual	St Resid
4	751.134	764.231	11.252	-13.097	-2.35R

Figure 4-5 ANOVA table for Total Ambulance Time (Output from MiniTab)

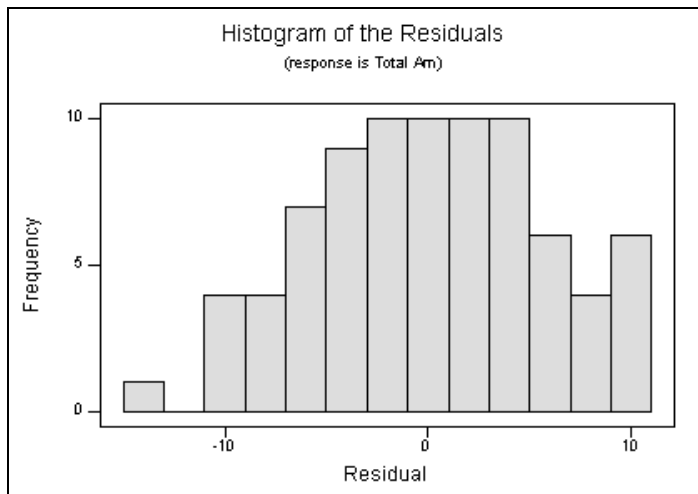


Figure 4-6 Histogram of Total Ambulance Time Residuals

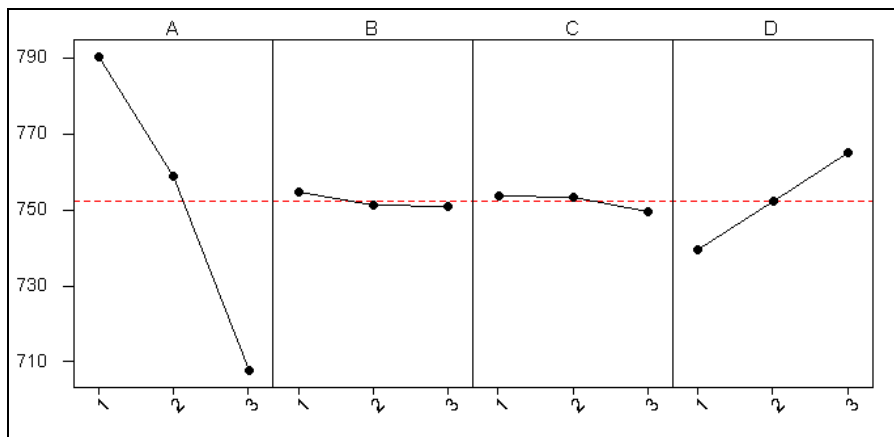
The F-value for *Volunteer Injury Rate*, is very high (299.55) indicating that the Total Ambulance Time is highly dependent upon the volunteer injury rate. The Main Effect plot



(Figure 4-7) shows that the Total Ambulance Time is significantly lower when the *Volunteer Injury Rate* is at Level 3 than it is at Level 1. This means that as the percentage of volunteers who are injured increases, the total ambulance time decreases. Initially this seems counter intuitive. However, and increase in the *Volunteer Injury Rate* increases the demand for an ambulance. As time goes on, the roadways are cleared and transportation within the region improves. This is simulated by decreasing the *Percent Destruction* over time. The velocity at which the ambulance transporters move is dependent upon the *Percent Destruction*. As time goes on, the velocity of the transporters will increase, decreasing the amount of time that it takes for each ambulance trip, and thus decreasing the average *Total Ambulance Time*.

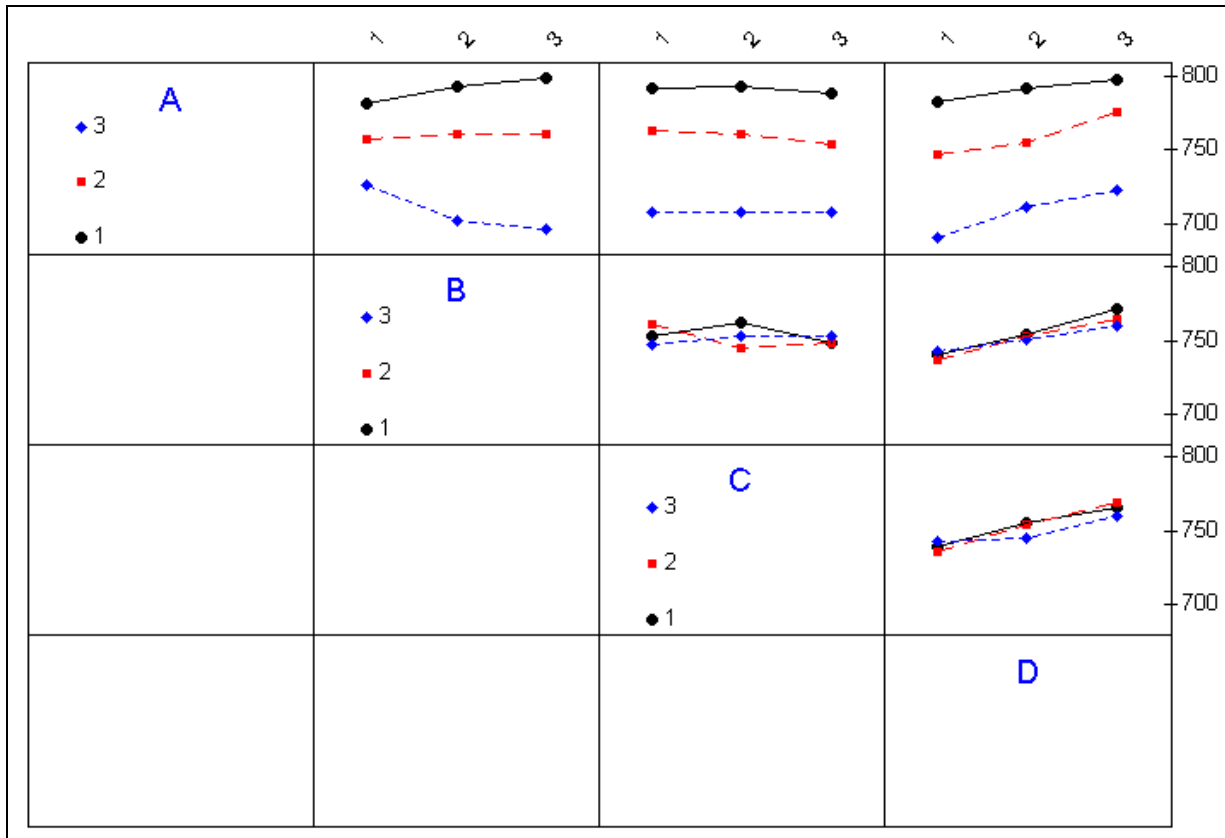
The values of *Injury Severity* and *Information Dissemination Rate* have virtually no effect on the Total Ambulance Time. This is evident by the very high p-value and a main effect plot that doesn't show much movement.

The value of *Transportation Decision* is directly related to the Total Ambulance Time. A high F-value (27.32) and the Main Effect Plot (Figure 4-7) demonstrate this. From the Main Effect Plot it appears that the Total Ambulance Time increases with increasing levels of *Transportation Decision*, this corresponds to increasing percentages of patients choosing the ambulance form of transportation. This is intuitive, since when the system has more victims, it is likely that the number of victims per ambulance will increase. This will increase the amount of time that is spent on the scene performing immediate triage procedures before transporting the patients to the hospital.



**Figure 4-7 Main Effects Plot for Total Ambulance Time**

The Interaction Plot shown in Figure 4-8 shows that most of the interaction effects are insignificant. The AB interaction is significant ( $p$ -value of 0.001) and it appears that this interaction is most prevalent when the *Volunteer Injury Rate* is high (Level 3) and the *Injury Severity* is low (Level 1) and results in a higher Total Ambulance Time value. In this situation, there are a high number of volunteers and most of the injuries sustained by victims are Level 1 and Level 2. Since the *volunteer injury rate* was at the default value of (0.7, 0.3, 0) this means that nearly all of the patients in the system would have Level 1 or Level 2 injuries, with only a very few sustaining Level 3 injuries. In this situation, more patients would be put in a single ambulance, and thus the amount of time spent on the scene would increase, which in turn increases the Total Ambulance Time.



**Figure 4-8 Interactions Plot for Total Ambulance Time**

### 4.2.2 Ambulance Wait Time

The Ambulance Wait Time is the amount of time that a patient spends waiting on an ambulance once they have decided they are going to seek ambulance transportation. From the ANOVA table in Figure 4-9 it can be seen that all four of the main effect factors contribute

significantly to the value of the Ambulance Wait Time. The interactions between *Volunteer Injury Rate* and *Injury Severity* and the three way interaction between *Volunteer Injury Rate*, *Injury Severity* and *Information Dissemination Rate* are also significant. The residual values are very low, and center around zero. A histogram of these values can be seen in Figure 4-10.

ANOVA Table: Ambulance Wait Time							
A=Volunteer Injury Rate B=Injury Severity							
C=Information Dissemination Rate D=Transportation Decision							
Source	DF	Seq SS	Adj SS	Adj MS	F	P	Significant?
A	2	6361.11	6361.11	3180.55	994.39	0.000	*
B	2	1946.04	1946.04	973.02	304.21	0.000	*
C	2	85.29	85.29	42.65	13.33	0.000	*
D	2	1776.94	1776.94	888.47	277.78	0.000	*
A*B	4	323.08	323.08	80.77	25.25	0.000	*
A*C	4	14.95	14.95	3.74	1.17	0.361	
A*D	4	30.56	30.56	7.64	2.39	0.094	
B*C	4	6.80	6.80	1.70	0.53	0.714	
B*D	4	30.96	30.96	7.74	2.42	0.091	
C*D	4	1.47	1.47	0.37	0.12	0.975	
A*B*C	8	78.42	78.42	9.80	3.06	0.027	*
A*B*D	8	26.97	26.97	3.37	1.05	0.439	
A*C*D	8	38.98	38.98	4.87	1.52	0.225	
B*C*D	8	27.16	27.16	3.39	1.06	0.435	
Error	16	51.18	51.18	3.20			
Total	80	10799.91					

Unusual Observations for Ambulance Wait Time					
Obs	Ambulanc	Fit	SE Fit	Residual	St Resid
4	26.7500	28.5606	1.6021	-1.8106	-2.28R
36	43.9818	42.1608	1.6021	1.8210	2.29R
54	33.4928	35.2369	1.6021	-1.7441	-2.19R

Figure 4-9 ANOVA table for Ambulance Wait Time (Output from MiniTab)

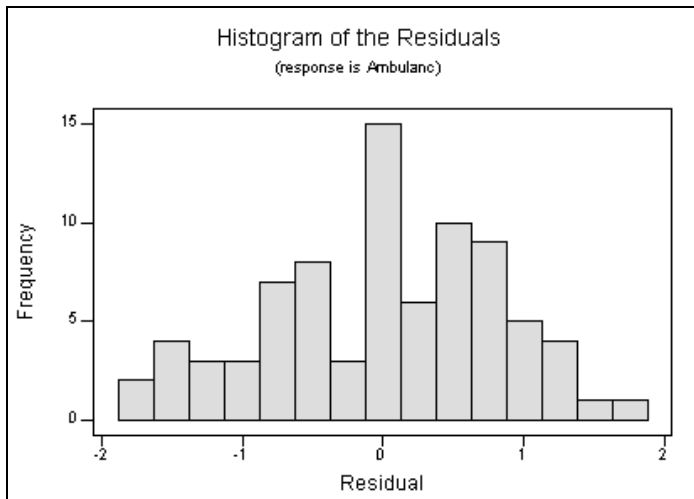
From the Main Effects plot (Figure 4-11), it can be seen that the Ambulance Wait Time increases with increasing values of *Volunteer Injury Rate*. This is intuitive, as the higher the *Volunteer Injury Rate* means more people needing medical assistant and consequently more people seeking ambulance transportation. As the number of people in queue for an ambulance increases, it is logical that the amount of time that they are spending waiting for the ambulance will also increase.

As the *Injury Severity* level increases, the Ambulance Wait Time decreases. Higher levels of *Injury Severity* have a higher portion of victims sustaining Level 2 and Level 3 injuries. One reason that this may decrease the Ambulance Wait Time is that as more victims sustain Level 3 injuries, more of them will die immediately upon impact of the disaster, resulting in fewer people

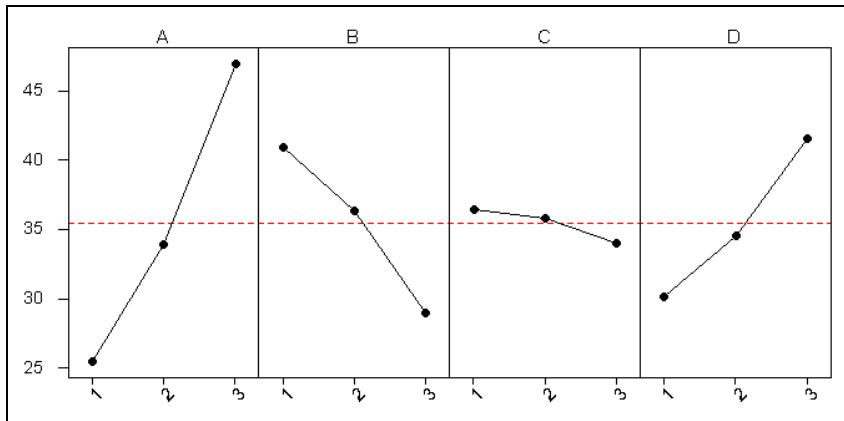
requiring medical attention. It is also possible that more of them will expire prior to seeking ambulance help, again resulting in a lower demand for ambulance transportation.

The *Information Dissemination Rate* has a significant but not a large effect on the Ambulance Wait Time. From the Main Effect Plot it can be seen that increasing values of the *Information Dissemination Rate* slightly reduce the Ambulance Wait Time. This is logical, since if people know about the Field Triage Location, they are less likely to seek immediate ambulance assistance and only a portion of those who go to the Triage Location will eventually require ambulance transportation.

The value of *Transportation Decision* has a large effect on the Ambulance Wait Time. As the level of the *Transportation Decision* increases, the Ambulance Wait Time increases. This can be explained by an increased percentage people choosing ambulance transportation, and thus a longer queue waiting for an ambulance to become available.

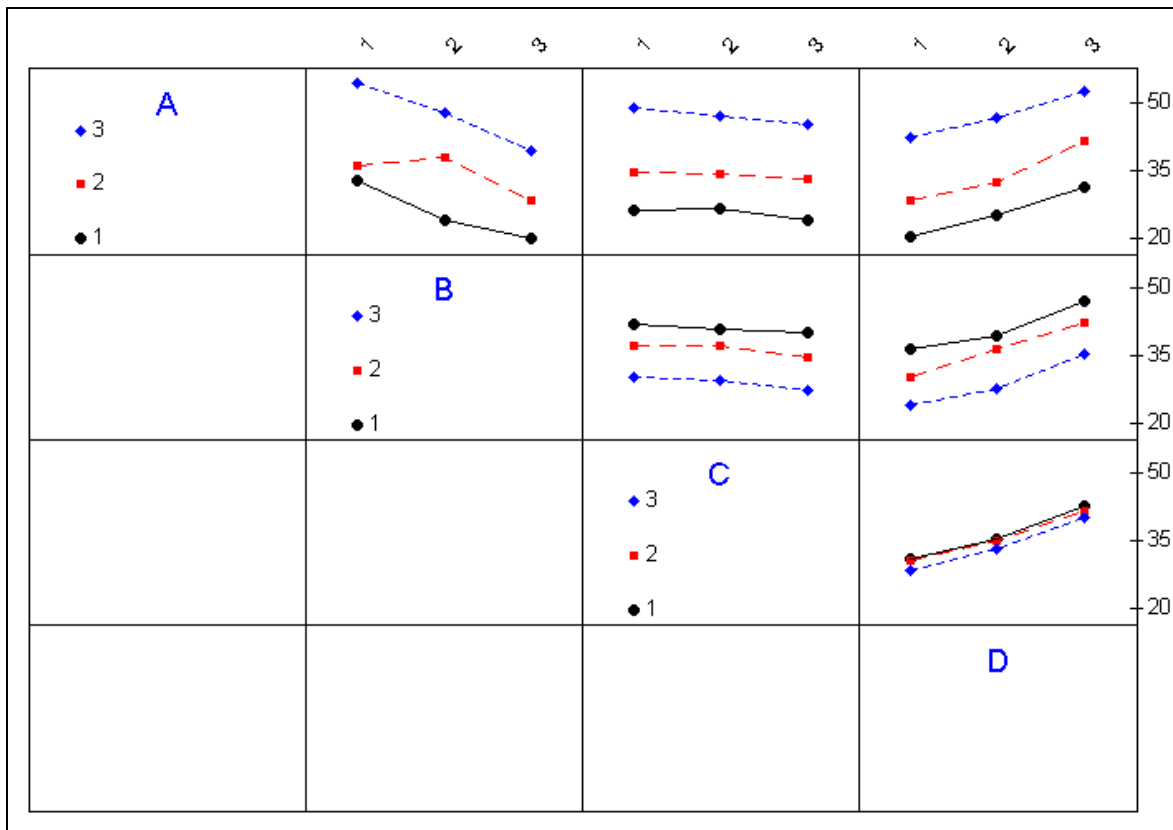


**Figure 4-10 Histogram of Ambulance Wait Time residuals**



**Figure 4-11 Main Effects Plot Ambulance Wait Time**

The interaction between *Volunteer Injury Rate* and *Injury Severity* was also found to be significant. From the Interaction Plot shown in Figure 4-12, it can be seen that the trend of the line produced when *Volunteer Injury Rate* is at Level 2, is different from that of the other two lines. When both *Volunteer Injury Rate* and *Injury Severity* are at their second level, the resulting Ambulance Wait Time is larger.



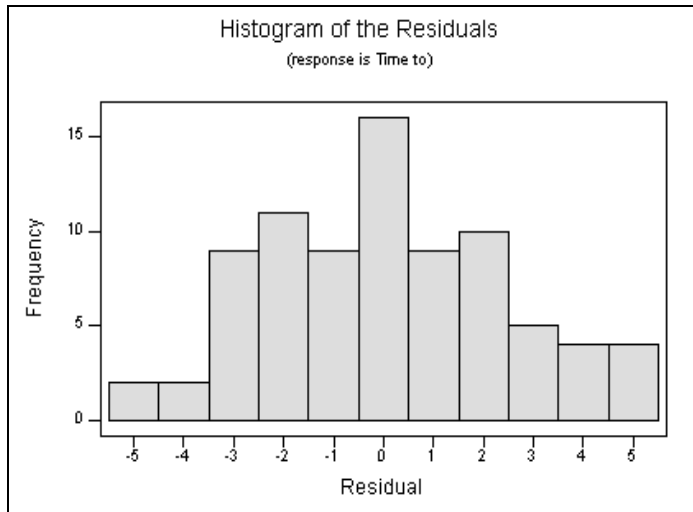
**Figure 4-12 Interaction Effects Ambulance Wait Time**

### 4.2.3 Time to arrival at hospital

The Time to arrival at hospital is the amount of time that it takes from when a patient begins seeking help to when they arrive at the hospital. This includes both the time that they spend waiting for the hospital and the time that it takes to be transported by ambulance to the hospital. From the ANOVA table in Figure 4-13 it can be seen that *Volunteer Injury Rate*, *Injury Severity* and *Transportation Decision* significantly affect the Time to arrival at hospital. At the alpha equals 0.05 level, *Information Dissemination Rate* does not have a significant affect. However, the *p*-value is quiet low (0.085) indicating that there may be some relationship. The interaction between *Volunteer Injury Rate* and *Injury Severity* is also significant. The residual values center around zero. Five of the eighty-one points were considered unusual due to large residual values. A histogram of these values can be seen in Figure 4-14.

ANOVA Table: Time to arrival at hospital							
A=Volunteer Injury Rate B=Injury Severity							
C=Information Dissemination Rate D=Transportation Decision							
Source	DF	Seq SS	Adj SS	Adj MS	F	P	Significant?
A	2	1310.19	1310.19	655.09	22.04	0.000	*
B	2	4008.82	4008.82	2004.41	67.44	0.000	*
C	2	171.36	171.36	85.68	2.88	0.085	
D	2	525.90	525.90	262.95	8.85	0.003	*
A*B	4	2312.39	2312.39	578.10	19.45	0.000	*
A*C	4	263.08	263.08	65.77	2.21	0.114	
A*D	4	147.01	147.01	36.75	1.24	0.335	
B*C	4	190.95	190.95	47.74	1.61	0.221	
B*D	4	190.99	190.99	47.75	1.61	0.221	
C*D	4	293.01	293.01	73.25	2.46	0.087	
A*B*C	8	448.41	448.41	56.05	1.89	0.133	
A*B*D	8	236.93	236.93	29.62	1.00	0.475	
A*C*D	8	204.58	204.58	25.57	0.86	0.567	
B*C*D	8	249.79	249.79	31.22	1.05	0.441	
Error	16	475.53	475.53	29.72			
Total	80	11028.93					
Unusual Observations for Time to arrival at hospital							
Obs	Time to	Fit	SE_Fit	Residual	St Resid		
1	294.502	289.179	4.884	5.323	2.20R		
16	310.288	305.104	4.884	5.184	2.14R		
22	291.252	286.151	4.884	5.100	2.10R		
24	280.020	285.439	4.884	-5.419	-2.24R		
55	289.118	294.303	4.884	-5.185	-2.14R		

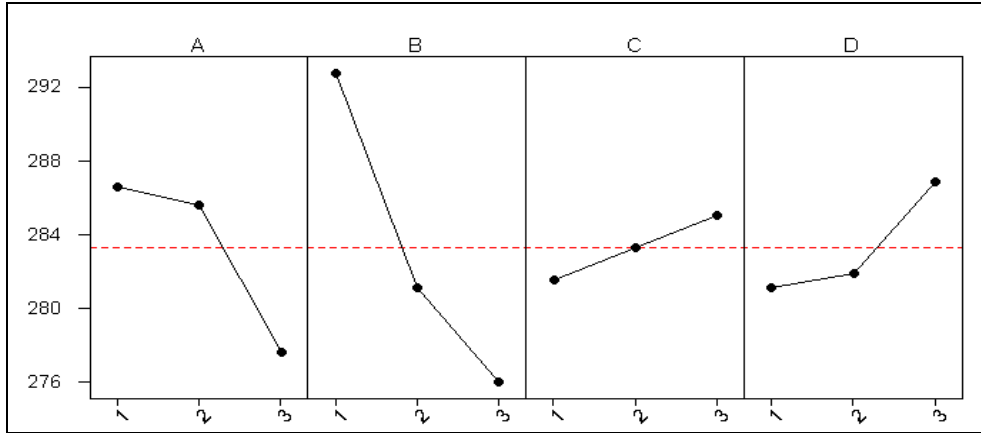
Figure 4-13 ANOVA table for Time to arrival at hospital (Output from MiniTab)



**Figure 4-14 Histogram of Time to arrival at hospital residuals**

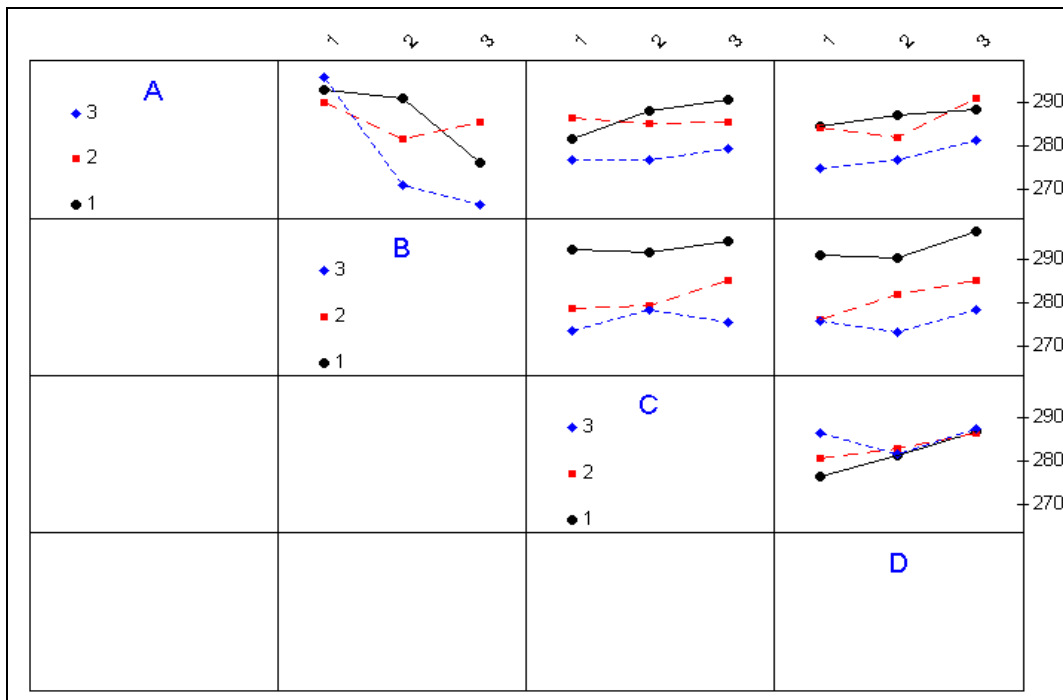
The main effects plot (Figure 4-15) indicates that as the *Volunteer Injury Rate* increases, the Time to arrival at hospital decreases. This response does not appear to be linear. As the *Volunteer Injury Rate* increases, the number of victims will increase, which one would think would increase the average Time to arrival at hospital; however, the statistics show otherwise. One explanation for this may be that since the volunteers that are injured are of Level 1 or Level 2 injury, more of them can be placed in a single ambulance, decreasing the amount of time that they spend waiting for an ambulance. Also, as the demand increases the amount of time over which ambulance trips are being made increases. The later ambulances will be able to drive much faster than the first ones because emergency crews will have cleared some of the debris from the roadways. This means that over time, the Time to arrival at hospital decreases. With an increased demand (caused by increasing the *Volunteer Injury Rate*), those who seek an ambulance at later times will have shorter Time to arrival at hospital values.

As the *Injury Severity* increases, the Time to arrival at hospital also decreases. A possible cause for this is a decrease in demand for ambulance transportation due to more of the victims sustaining Level 3 injuries, resulting in a larger portion being dead on impact. A higher *information dissemination rate* results in a slightly higher Time to arrival at hospital, although as stated previously, according to the *p*-value this effect is statistically insignificant. Moving from the second to the third *Transportation Decision* level results in a large increase in the Time to arrival at hospital. This is intuitive as the third level of *Transportation Decision* results in a much greater demand for ambulance transportation.



**Figure 4-15 Main Effects Plot Time to arrival at hospital**

The interaction effect between *Volunteer Injury Rate* and *Injury Severity* was also found to be statistically significant. From the Interactions plot in Figure 4-16, it is evident that the Time to arrival at hospital is greatly dependent upon the relationship between the two variables. The values of each of these variables will have an affect on the total demand for ambulances as well as the mixture of levels of injury. Together these effects can combine to have a larger impact, or cancel each other out, depending on the selected values.



**Figure 4-16 Interactions Plot for Time to arrival at hospital**



### 4.3 Comparison to actual events

The output of the simulation was compared to the actual events that occurred after the May 4, 2007 Greensburg tornado to see how close the simulation was to reality. This comparison is not perfect, as the decision rules used in the simulation are not necessarily the decision rules used by the Emergency Management team in Kiowa County. Even if the rules were precisely what was stated in their response plan, there is always the possibility that the plan was not be enacted properly.

A total of 12 fatalities were reported, with 10 of these being immediate and 2 occurring later (One 4 days later and the other 9 days later). In the twenty-four hours following the tornado, approximately 20 ambulances arrived at Greensburg, 10-15 of which were active (Ablah 2007). Statistics for the total number of injuries requiring medical attention are not consistent. In the report published by Ablah, 90 people arrived at area hospital emergency departments seeking help during the twenty-four hours following the tornado. According to the report, 59 of these patients were treated at Pratt Regional Medical Center. An interview with Sherry Besser, a director at Pratt Regional Medical Center, revealed that 102 tornado victims were treated at Pratt Regional Medical Center alone; 72 of these were within the first 9 hours, 85 were injured directly by the tornado and 17 were workers injured during rescue efforts. Assuming that the numbers reported from each of the other hospitals were accurate and making adjustments for those treated at Pratt Regional Medical Center, the total number of injuries would be brought to 133 victims.

When the simulation was run for five replications, each consisting of a twenty-four hour run length, the following results in Figure 4-17 were obtained. The simulation was initialized as described in section 3.2.1. The values for the factors that the sensitivity analysis was performed on were all set to Level 2. While the results were not completely off from what actually occurred in Greensburg, it was very obvious that the injury severities were off, as none of the 95% Lower Confidence Limit (LCL) and Upper Confidence Limit (UCL) contained the value from the Greensburg actual occurrence. The values of these confidence intervals can be seen in Figure 4-17. The Total Injuries and First arrival at hospital were within the confidence range, as was the maximum number of ambulances that were activated. In the Figure, a \* beside the statistic indicates that it did not fall within the confidence range.

Simulation Statistics									
All Factors at Level 2									
Statistic	Replication 1	Replication 2	Replication 3	Replication 4	Replication 5	Average	UCL	LCL	Greensburg
First Arrival at hospital	167	143	167	150	251	175.6	213.68387	137.51613	195
Last Arrival at hospital*	328	465	493	439	495	444	504.28921	383.71079	540
Total Injuries	120	121	135	125	129	126	131.40325	120.59675	90-133
Total Dead on Scene*	24	18	17	15	25	19.8	23.690417	15.909583	10
Total Dead Later*	0	1	0	1	2	0.8	1.5333514	0.0666486	2
Level 3 Injuries*	25	24	22	19	31	24.2	28.090417	20.309583	12
Level 2 Injuries*	35	28	36	41	34	34.8	38.883128	30.716872	30
Level 1 Injuries*	59	68	76	64	63	66	71.646601	60.353399	72
Max Ambulances Active	13	14	19	24	18	17.6	21.450718	13.749282	20

**Figure 4-17 Simulation statistics compared to Greensburg statistics, all factors at Level 2**

Since the injury mix seemed to be skewed, the simulation was run again. This time the *Injury Severity* variable was set to the first level from the DOE. This value has a smaller percent of people being severely injured. The results from this are shown in Figure 4-18. In this case, the simulation aligned much better with the actual occurrence. The number of people who died later was much lower than the actual occurrence and fewer ambulances were activated than what actually occurred. These can be explained by the fact that both of the people who died after the initial impact in Greensburg died more than 24 hours after the disaster, thus it would have been outside of the period of this simulation. According to an interview with Sherri Besser, one of them died 9 days later. The other died 4 days later. In Ablah’s Regional Health System Response to the Greensburg EF5 Tornado, she reports that 20 ambulances made themselves available within the first 24 hours, but only 10 to 15 were active. This simulation model assumes that only requested ambulances arrive at the scene, and that ambulances are only requested if they are needed. In the model, the average Max Ambulances Active was 15, which goes along with the number of ambulances that were actually being used during Greensburg. The other statistics were all within the appropriate ranges.

Simulation Statistics									
All Factors at Level 2, Except Injury Severity at Level 1									
Statistic	Replication 1	Replication 2	Replication 3	Replication 4	Replication 5	Average	UCL	LCL	Greensburg
First Arrival at hospital	177	168	240	168	230	196.6	227.64919	165.55081	195
Last Arrival at hospital	496.86	322.58	461.8	682.49	509.92	494.73	607.49957	381.96043	540
Total Injuries	120	121	131	125	128	125	129.06427	120.93573	90-133
Total Dead on Scene	10	10	9	8	11	9.6	10.599389	8.6006105	10
Total Dead Later*	0	1	0	0	0	0.2	0.5919928	-0.1919928	2
Level 3 Injuries	11	13	12	10	12	11.6	12.599389	10.600611	12
Level 2 Injuries	31	20	27	31	31	28	32.203654	23.796346	30
Level 1 Injuries*	77	87	91	83	84	84.4	88.937645	79.862355	72
Max Ambulances Active*	14	13	17	16	15	15	16.385904	13.614096	20

**Figure 4-18 Simulation statistics compared to Greensburg statistics, all factors at Level 2, Injury Severity at Level 1**

## 4.4 Evaluating Decision Rules

The decisions rules for when to request more ambulances and when to release the ambulances that are currently providing their assistance are very critical. These decisions will determine how quickly victims receive medical attention and how much risk outside districts are being put at by lending their ambulances to disaster relief. A balance between quick medical response and an acceptable level of risk must be found.

There are infinite many decision rules that could be tested. However, for this paper the decision rules tested will be limited. The decision of when to request more ambulances is currently based on the expression:

$$\frac{1}{2} * \frac{\text{Max}(\text{TAVG}(\text{TotalAmbulanceTime}), 30)}{\text{TAVG}(\text{TimeBetweenHelpSought})} > \text{MT}(\text{Ambulance}) + \sum_{\# = 1}^8 \text{OD}\# \text{InrouteDisaster}$$

The  $\frac{1}{2}$  at the beginning of the expression is based on the assumption that ambulances will be transporting multiple victims in one ambulance load. It considers the average number of victims transported in a single ambulance to be two. Changing this value would change the number of ambulances requested.

Another method of changing the decision rule is to give the outside districts more control over how many ambulances they send. Creating the criteria that an ambulance district will not send an ambulance if their current coverage is below 50% allows outside ambulance districts to protect themselves. This may also have a significant impact on the overall system performance.

Finally, the order in which ambulances are requested from districts is important. Currently, an ambulance is requested from the outside district with the highest percent coverage, with those closest in distance being considered first. Another method would be to take all of the available ambulances in order of distance to the disaster. This will result in the districts close to the disaster carrying the majority of the risk.

Ambulances are released based upon the expression:

$$(\text{NT}(\text{ambulance})/\text{MT}(\text{ambulance})) < \text{Release Rule}$$

By changing the value of Release Rule, the time at which the ambulance is released to go back home may be changed. The default value for this has been 0.80. Other values will be tested to see how they impact the system performance.

To evaluate decisions rules, the simulation was run with the input from Greensburg, with the variables that were evaluated during the DOE set at their Level 2 values, except for the *Injury*

Severity which was put to its Level 1 value. This is the configuration of the system that was found to fit what actually occurred at Greensburg well. Each of the decision rules were run for 5 replications, so that paired t-tests could be performed on the output. For this paper, 5 replications seemed sufficient to show the capability of the simulation to test decision rules. If decision rules were really going to be tested and enacted into a disaster response plan, performing more replications would improve the quality of the results. The decision rules listed in Table 4-11 were evaluated.

**Table 4-11 Decision Rules**

<b>Decision Rule</b>	<b>Expression</b>
Request Rule 1	$\frac{1}{2} * \frac{Max(TAVG(TotalAmbulanceTime),30)}{TAVG(TimeBetweenHelpSought)} > MT(Ambulance)$
Request Rule 2	$\frac{1}{3} * \frac{Max(TAVG(TotalAmbulanceTime),30)}{TAVG(TimeBetweenHelpSought)} > MT(Ambulance)$
Request Rule 3	$\frac{1}{2} * \frac{Max(TAVG(TotalAmbulanceTime),30)}{TAVG(TimeBetweenHelpSought)} > MT(Ambulance)$ AND Coverage > 0.50
Request Rule 4	$\frac{1}{2} * \frac{Max(TAVG(TotalAmbulanceTime),30)}{TAVG(TimeBetweenHelpSought)} > MT(Ambulance)$ AND Coverage > 0.50 AND requested in order of distance, closest first
Request Rule 5	$\frac{1}{2} * \frac{Max(TAVG(TotalAmbulanceTime),30)}{TAVG(TimeBetweenHelpSought)} > MT(Ambulance)$ AND requested in order of distance, closest first
Release Rule 1	$(NT(ambulance)/MT(ambulance)) < Release Rule$ Release Rule=0.80
Release Rule 2	$(NT(ambulance)/MT(ambulance)) < Release Rule$ Release Rule=0.90
Release Rule 3	$(NT(ambulance)/MT(ambulance)) < Release Rule$ Release Rule=1.00

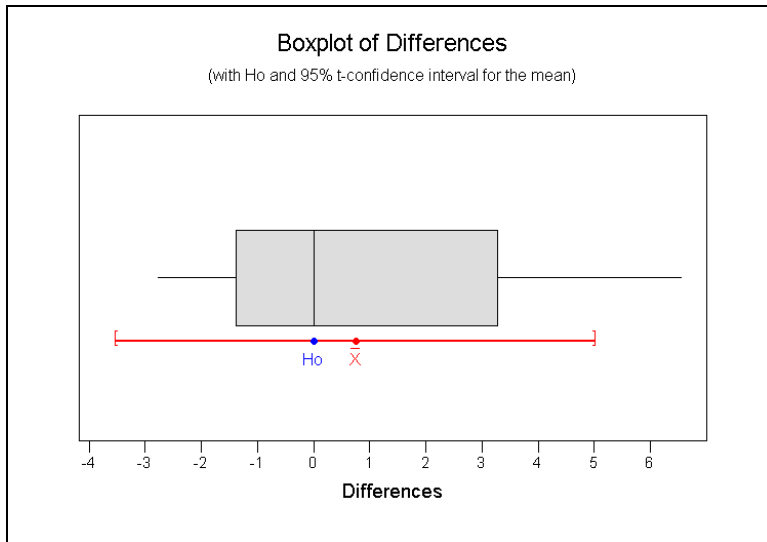
Results from Request Rules and Release Rules								
Request Rule	Release Rule	Replication	Average			Average Coverage	Average Minimum % Coverage	Average % Time Coverage<50%
			Ambulance Wait Time	Max Arrival Time	Deaths			
1	1	1	47.537	491.860	0.000	0.852	0.205	0.145
		2	53.283	322.580	1.000	0.841	0.308	0.204
		3	48.452	461.800	0.000	0.786	0.000	0.142
		4	32.301	682.490	0.000	0.852	0.197	0.147
		5	42.725	509.920	0.000	0.816	0.131	0.213
		AVERAGE	44.860	493.730	0.200	0.829	0.168	0.170
1	2	1	47.537	461.260	0.000	0.846	0.205	0.143
		2	53.283	334.130	1.000	0.846	0.308	0.190
		3	48.452	461.800	0.000	0.786	0.000	0.142
		4	25.759	682.490	0.000	0.828	0.197	0.148
		5	45.491	509.920	0.000	0.820	0.131	0.138
		AVERAGE	44.104	489.920	0.200	0.825	0.168	0.152
1	3	1	44.495	387.210	0.000	0.853	0.205	0.120
		2	45.394	398.100	1.000	0.847	0.308	0.176
		3	51.627	496.030	0.000	0.818	0.000	0.142
		4	28.261	682.490	0.000	0.854	0.197	0.140
		5	37.581	540.850	0.000	0.817	0.131	0.138
		AVERAGE	41.472	500.936	0.200	0.838	0.168	0.143
2	1	1	70.787	299.670	0.000	0.874	0.131	0.069
		2	59.641	400.500	1.000	0.765	0.155	0.065
		3	46.907	347.330	0.000	0.834	0.155	0.143
		4	42.364	462.090	0.000	0.850	0.163	0.086
		5	39.423	417.390	0.000	0.702	0.285	0.140
		AVERAGE	51.824	385.396	0.200	0.805	0.178	0.100
3	1	1	64.888	428.680	0.000	0.898	0.472	0.035
		2	55.361	425.300	1.000	0.894	0.476	0.036
		3	61.627	424.840	0.000	0.843	0.476	0.052
		4	42.364	648.160	0.000	0.898	0.476	0.042
		5	49.328	641.800	0.000	0.793	0.474	0.052
		AVERAGE	54.714	513.756	0.200	0.865	0.475	0.043
4	1	1	65.680	338.710	0.000	0.886	0.476	0.067
		2	59.050	338.740	1.000	0.889	0.476	0.092
		3	51.881	461.800	0.000	0.815	0.476	0.055
		4	34.907	648.160	0.000	0.873	0.476	0.089
		5	51.324	494.960	0.000	0.812	0.476	0.052
		AVERAGE	52.568	456.474	0.200	0.855	0.476	0.071
5	1	1	47.764	368.070	0.000	0.850	0.250	0.133
		2	41.847	417.110	1.000	0.832	0.317	0.204
		3	48.548	461.800	0.000	0.787	0.000	0.142
		4	24.798	496.870	0.000	0.837	0.229	0.134
		5	43.069	470.270	0.000	0.818	0.125	0.138
		AVERAGE	41.205	442.824	0.200	0.825	0.184	0.150

Figure 4-19 Results from Simulating Request Rules and Release Rules

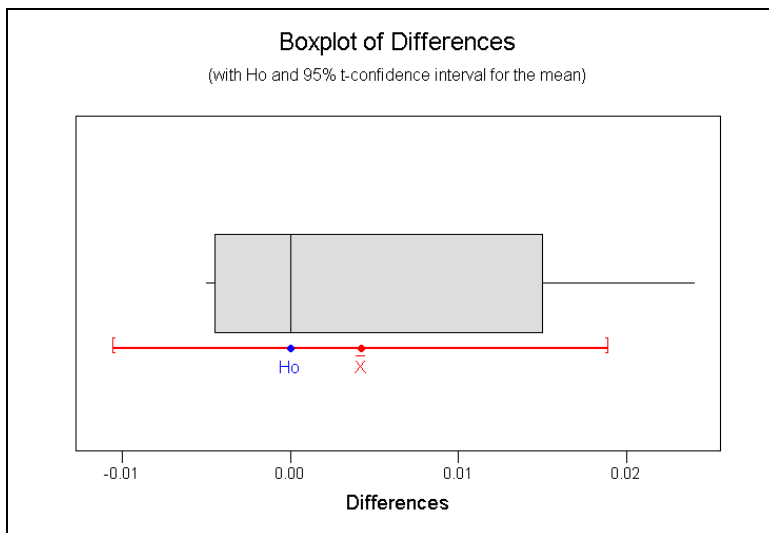
The default decision rules that were used for all of the analysis previously done on the system were Request Rule 1 and Release Rule 1. This will be used as the standard to which all of the other decision rules are compared. From the chart in Figure 4-20, it is obvious that none of the decision rules have an impact on the number of deaths. Average Ambulance Time, Average Coverage and Average Percent of Time that Coverage is less than 50% will be used to evaluate the performance of the systems under the various decision rules. The desire is to minimize Average Ambulance Time and the average percent of time that coverage is less than 50%, while maximizing the Average Coverage. Paired t-tests will be used to determine if the decision rules have a significant impact on the performance of the system.

### ***Request Rule 1, Releases Rule 2***

Request Rule 1 and Release Rule 2 change the default system by increasing the percentage that is used in the release rule expression. This will allow for ambulances to be released and sent home more quickly, since they are released as soon as the utilization drops below the specified percentage (90%). When Request Rule 1 and Release Rule 2 were implemented, the resulting average Ambulance wait time was 44.104 minutes compared to the default decision rule average of 44.860 minutes. The paired t-test found that the difference in means is statistically insignificant, as the box plot in Figure 4-20 shows. The average percent coverage dropped from 82.9% to 82.5%. This is also statistically insignificant. A box plot of the differences in average percent coverage can be found in Figure 4-21.

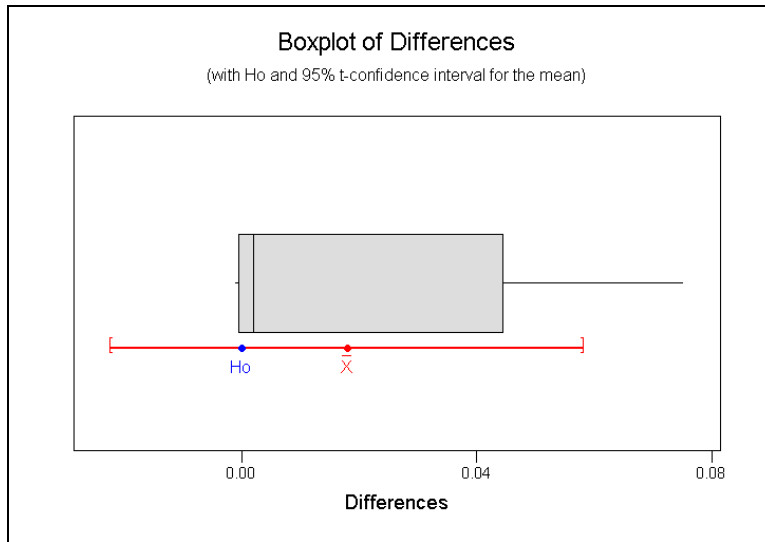


**Figure 4-20** Box-plot of the Differences from paired T-test on Ambulance Wait time



**Figure 4-21** Box-plot of the differences from paired t-test on average percent coverage

The percent of time that the coverage is less than 50% dropped from 17% to 15.2% (4 hours and 4 minutes to 3 hours and 38 minutes). The resulting confidence interval for the mean difference is -0.0223 to 0.0583, with the mean difference falling at 0.0145. Since the confidence interval contains zero and a p-value of 0.282 indicates that the difference is statistically insignificant. A box plot of this can be seen in Figure 4-22.

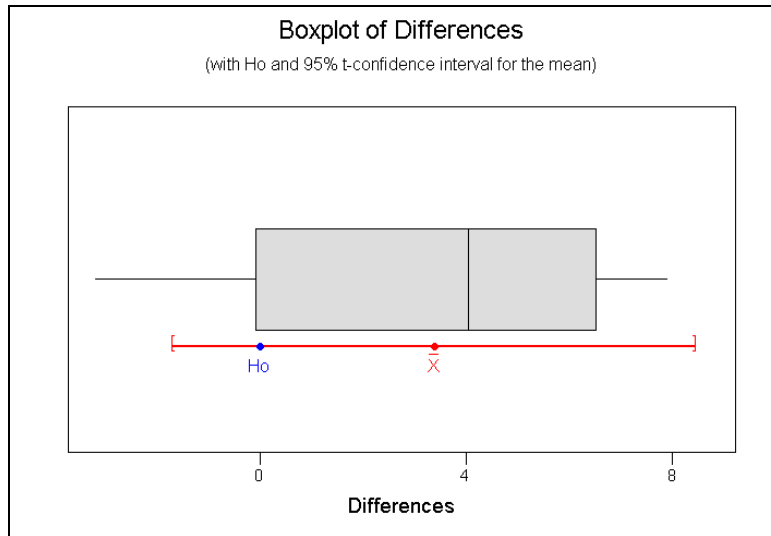


**Figure 4-22 Box-plot of the differences from paired T-test on Percent of time that coverage is less than 50%**

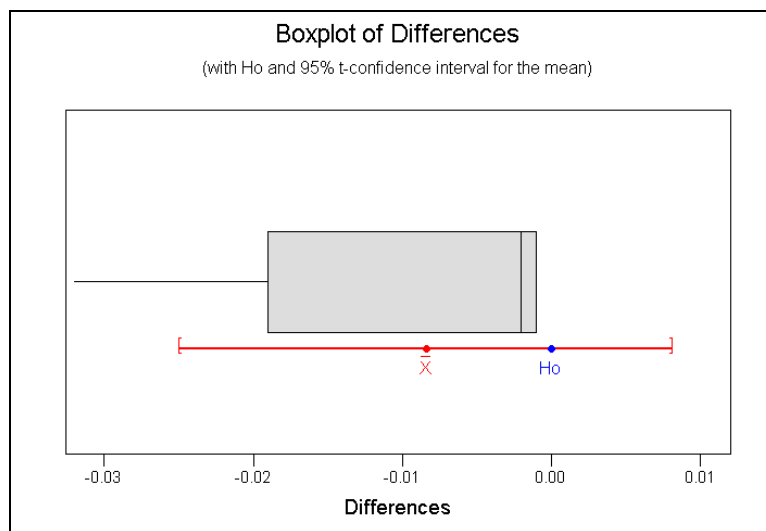
### ***Request Rule 1, Releases Rule 3***

Request Rule 1 and Release Rule 3 change the default system by increasing the percentage that is used in the release rule expression to 100%. This will allow for ambulances to be released and sent home more quickly, since they are released as soon as the utilization drops below 100%. Since the release process involves checking that the release rule is met twice, with a ten minute delay between checks, before releasing an ambulance to return to its home district, ambulances will not be sent home the first instant that they are not allocated to a victim entity. When Request Rule 1 and Release Rule 3 were implemented, the resulting average Ambulance wait time was 41.472 minutes compared to the default decision rule average of 44.860 minutes. The paired t-test found that the difference in means is statistically insignificant, as the box plot in Figure 4-23 shows. The p-value for this test was 0.138. The average percent coverage increased from 82.9% to 83.8%. This is also statistically insignificant, with a p-value of 0.232. A box plot of the differences in average percent coverage can be found in Figure 4-24.



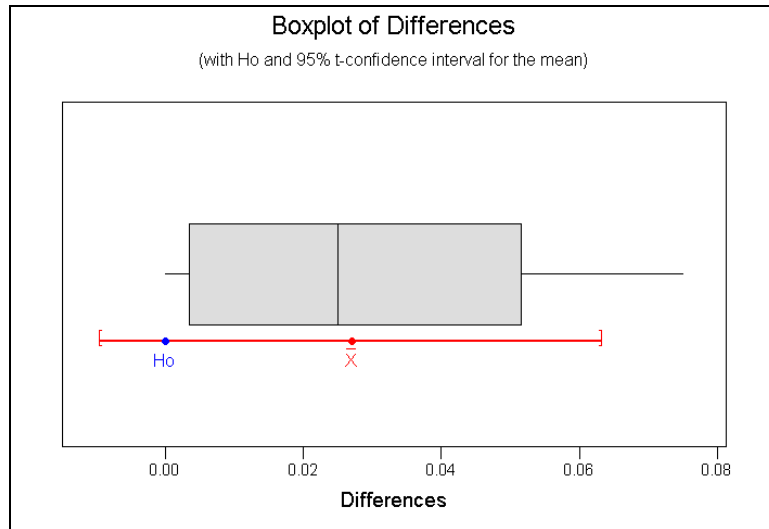


**Figure 4-23** Box-plot of the differences from paired T-test on average ambulance wait time



**Figure 4-24** Box-plot of the differences from paired T-test on average percent coverage

The average percent of time coverage is less than 50% decreased from 17.02% to 14.32% (4 hours and 4 minutes to 3 hours and 26 minutes). At the 95% confidence level, this is also insignificant with a p-value of 0.109. This is shown in Figure 4-25. More replications could be run to determine if there is in-fact a difference in the means. With 5-replications, none of the output statistics were found to experience a significant change due to this decision rule.

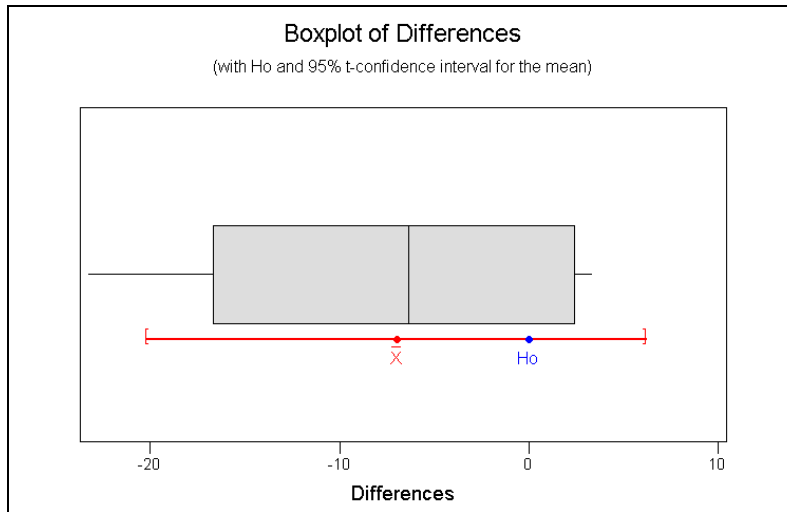


**Figure 4-25 Box-plot of differences from paired T-test on average percent of time coverage is less than 50%**

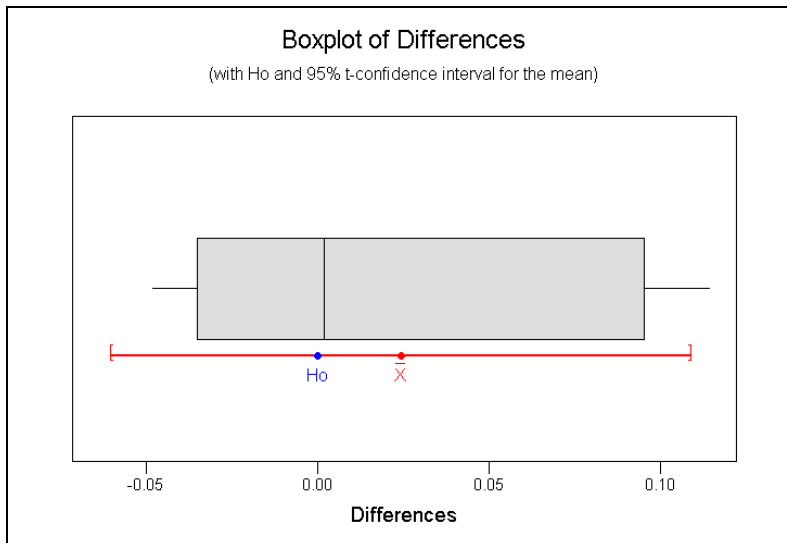
### ***Request Rule 2, Release Rule 1***

Request Rule 2 and Release Rule 1 changes the request rule by increasing the assumed number of victims transported per ambulance trip from 2 to 3. This results in fewer ambulances being requested initially. The Release rule is not changed from that of the default system. A paired t-test on the difference average ambulance wait time showed that the increase in wait time from 44.86 minutes to 51.824 minutes is statistically insignificant. A paired t-test on average percent coverage indicates that its difference is also insignificant. However, the average percent of time that coverage is less than 50% decreases from 17% to 10%, which as shown in Figure 4-28 is statistically significant at the 95% confidence level. The resulting p-value is 0.035.

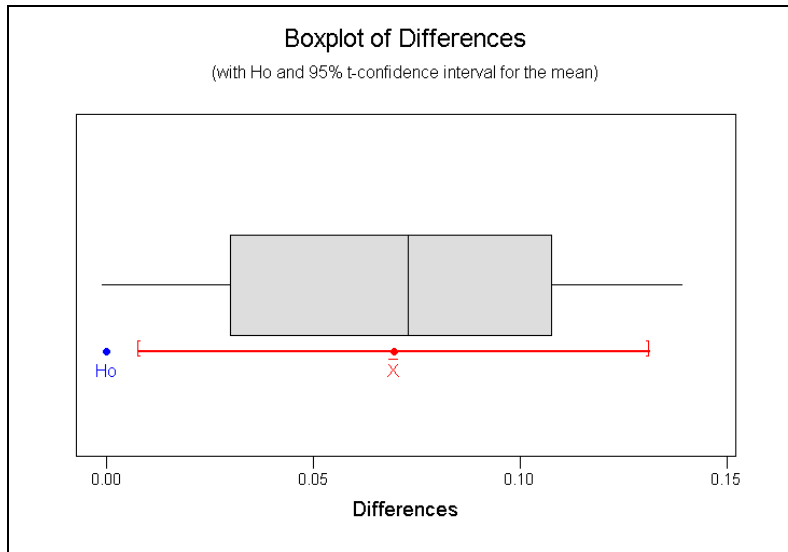
This system of decision rules appears to be superior to the default system. It decreases the risk taken on by outside districts by decreasing the portion of time that they have less than 50% coverage. It does this without significantly increasing the average ambulance wait time. Running more replications of each of these systems would provide a stronger assurance that the increase in ambulance wait time is in fact insignificant.



**Figure 4-26** Box-plot of difference for paired t-test of average ambulance wait time



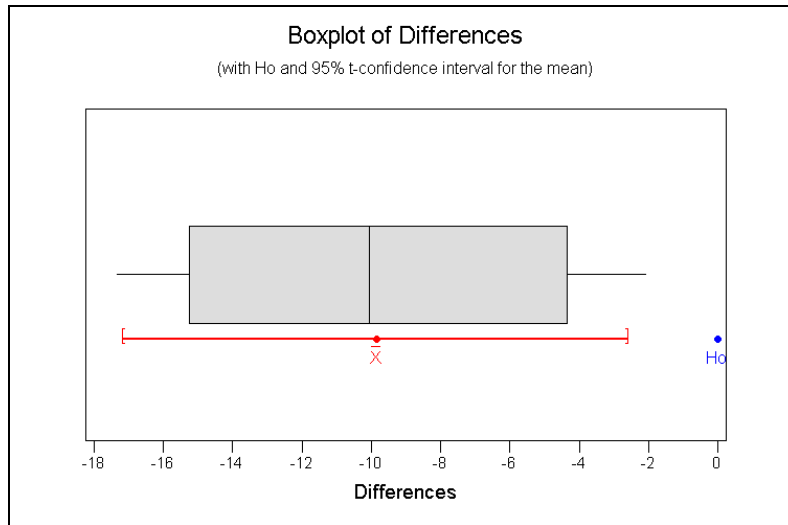
**Figure 4-27** Box-plot of differences for paired t-test of average percent coverage



**Figure 4-28 Box-plot of differences for paired t-test of average percent of time coverage is less than 50%**

### ***Request Rule 3, Releases Rule 1***

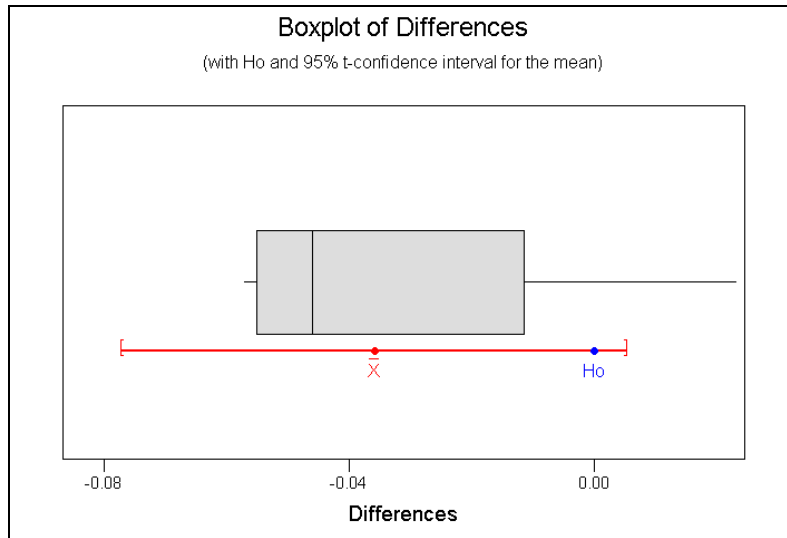
This system of decision rules uses the same request rule as the default system, but gives more control to the outside ambulance district to protect them self from undo risk. It allows for them to not send any more ambulances if their *Percent Coverage* is currently at or below 50%. This means that at worst, the district will maintain one less than 50% of their fleet of ambulances. As would be expected, this results in an increase in the average ambulance wait time, from a mean of 44.86 minutes to a mean of 54.71 minutes, and increase of approximately 10 minutes. A box-plot of the differences can be seen in Figure 4-29. The difference is statistically significant with a p-value of 0.02.



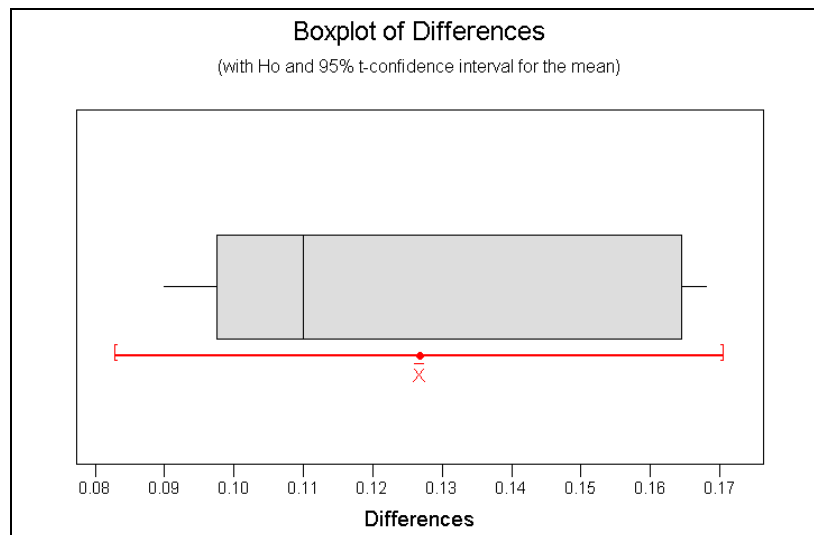
**Figure 4-29 Box-plot of difference for paired t-test of average ambulance wait time**

The mean average percent coverage increased from 82.9% to 86.5%. A box-plot of the differences is shown in Figure 4-30. At the 95% confidence interval, the difference is statistically insignificant; however, a p-value of 0.074 suggests that it is possible that if more replications were run, then it may be found to be significant. The difference in percent of time that coverage is less than 50% is much greater, with a mean decrease of 12.68%. Figure 4-31 shows the box-plot of differences and the resulting (0.083, 0.17) confidence interval, which indicates that implementing this decision rule will decrease the average percent of time that coverage is below 50% by 8.3-17%. That is a difference of 2-4 hours of coverage below 50%. This is a very significant improvement to the level of risk that is taken on by outside ambulance districts.

This system of decision rules increases the average ambulance wait time by 2-18 minutes, but decreases the percent coverage below 50% by 8-17%. Emergency Management officials would have to decide if they believe that the decrease in risk is worth the increase in ambulance wait time.



**Figure 4-30** Box-plot for difference of paired t-test of average percent coverage

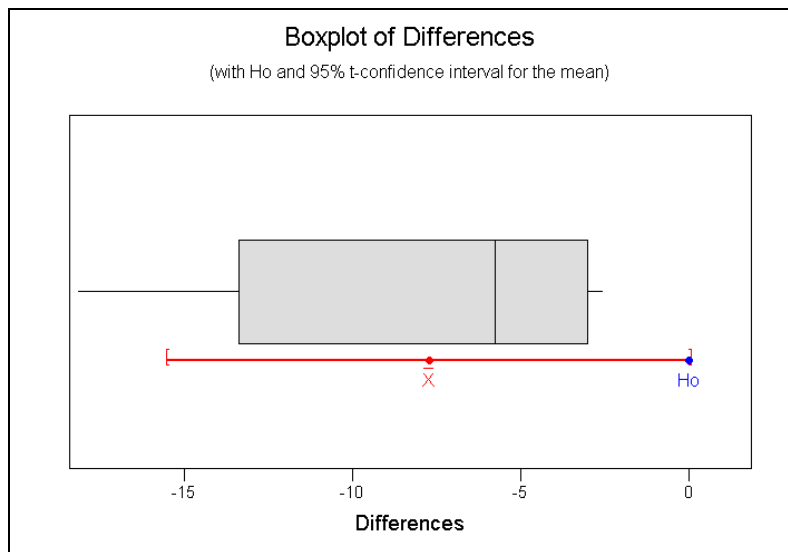


**Figure 4-31** Box-plot for difference of paired t-test of average percent of time coverage is less than 50%, the resulting p-value for the difference in means was 0.001

### ***Request Rule 4, Releases Rule 1***

Request Rule 4 maintains the default request rule, adds the criteria that ambulances will not be released if the percent coverage is already at or below 50% and it changes the order in which ambulances are requested from districts. Under the default system, the district with the highest *percent coverage* is the one that the ambulance is requested from. Under Request Rule 4, ambulances are requested based solely upon distance to the disaster area. Thus, all of the

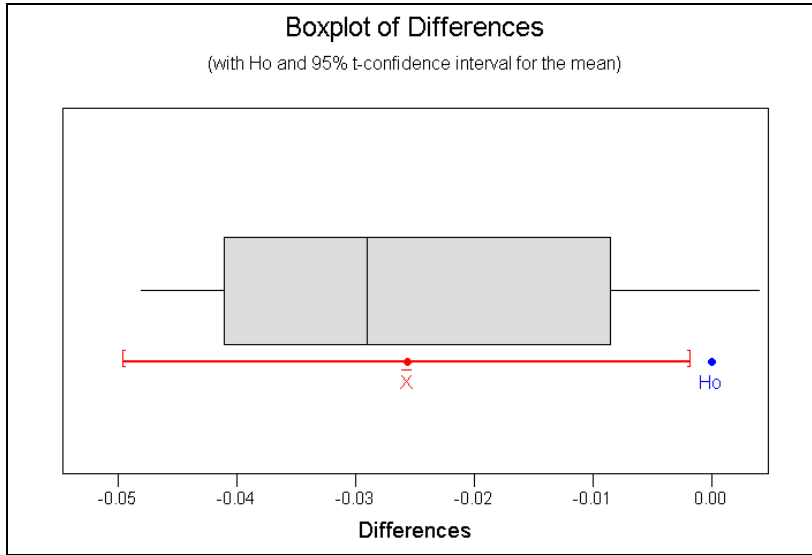
ambulances from OD 1 would be requested until its *percent coverage* fell below 50%, then ambulances from OD 2 would be requested until its *percent coverage* fell below 50%, then ambulance from OD 3 would be requested, and so on until all the ambulances that are needed are requested. The release rule is maintained the same as with the default system. The result is an increase in the mean average ambulance wait time from 44.86 to 52.57 minutes. The resulting 95% confidence interval for the mean difference is (-15.51, 0.09), with a p-value of 0.052. At 95% confidence level, this difference is considered statistically insignificant, but from looking at the p-value it is likely that there is in fact a difference in means. Running more replications of these systems would improve the accuracy of the confidence interval. This increase in ambulance wait time is possibly because ambulances that are farther away are requested last, and thus they will not arrive on the scene as early.



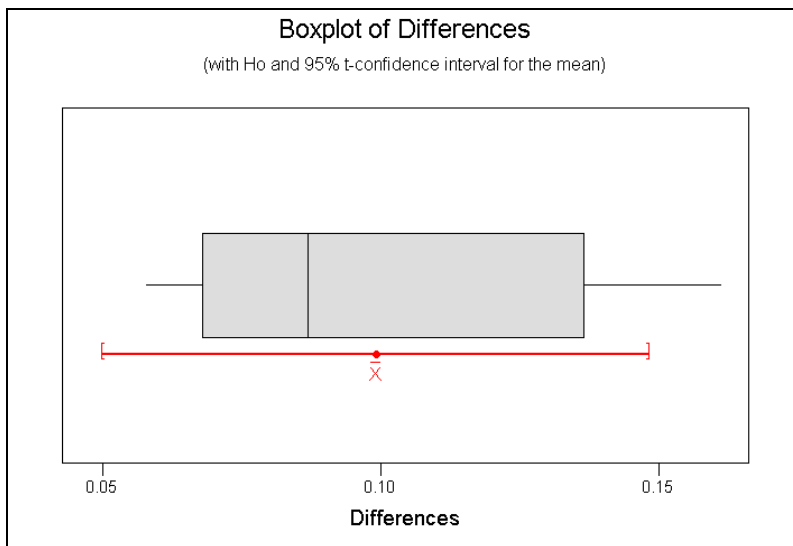
**Figure 4-32 Box-plot of differences for paired t-test of average ambulance wait time**

The mean average percent coverage increased from 82.94% to 85.5%. With a p-value of 0.41, this difference is statistically significant (Figure 4-33). The resulting improvement in coverage is 1.7-4.9%. The difference in the percent coverage less the 50% is more dramatic. The mean decreased from 17% to 7.1%, decreasing the average time that a district has less than 50% coverage from 4 hours to 1.7 hours. The p-value on this test is 0.005. The large improvement in percent coverage below 50% is a result of great improvements for the districts that are farthest away from the disaster zone. If the coverage for districts that are far from the disaster drops below 50%, then it will stay below 50% for a long time because of the large travel times. With

this request rule, the ambulances that are farther from the disaster area are less likely to be called into duty.



**Figure 4-33** Box-plot of differences from paired t-test of average percent coverage



**Figure 4-34** Box-plot of differences from paired t-test of average percent of time coverage is less than 50%

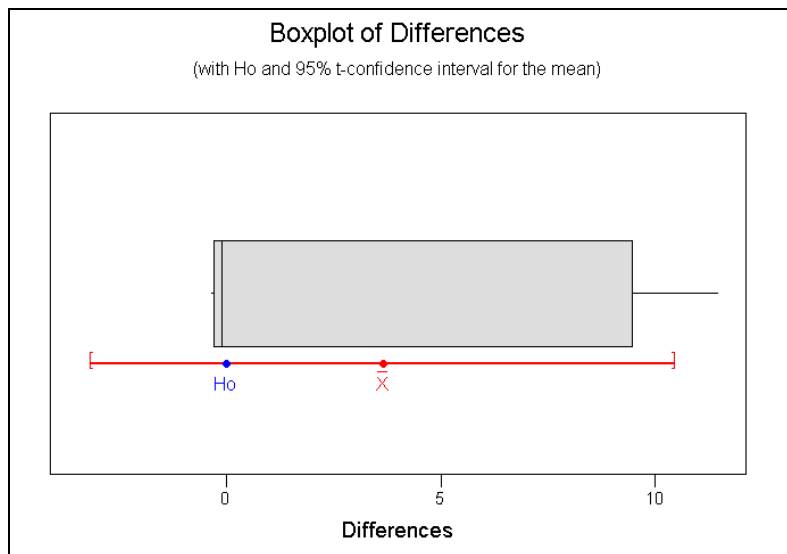


### ***Request Rule 5, Releases Rule 1***

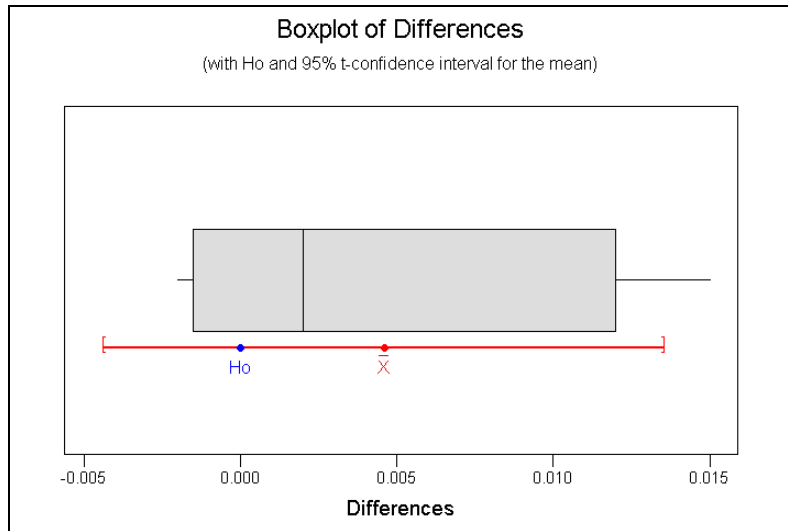
Request Rule 5 is similar to Request rule 4, except it does not require that *percent coverage* be greater than 50% to dispatch an ambulance. It has the same decision rule as the default system, but prioritizes the requests based upon shortest distance to the disaster scene instead of maximum percent coverage. This shifts even more of the burden onto the districts that are near the disaster than was done by Request Rule 4. The Release Rule remains the same as that used in the default system.

The mean average ambulance wait time decreased from 44.86 minutes to 41.21 minutes. The p-value from the paired t-test was 0.211 with a confidence interval on the difference in means being (-3.16, 10.47) indicating that this difference is not statistically significant (Figure 4-35). The mean average coverage went from 82.94% to 82.48%, with a p-value of .228 this difference is considered statistically insignificant. A box-plot of the difference in percent coverage is shown in Figure 4-36. The mean percent coverage below 50% decreased from 17% to 15% (4 hours and 4 minutes to 3 hours and 36 minutes). The resulting p-value of .227 indicated that this difference is not statistically significant (Figure 4-37).

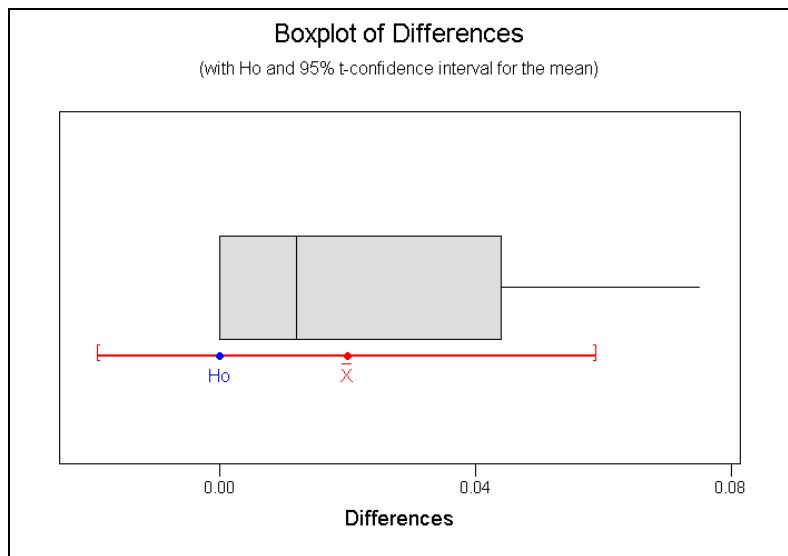
This system of decision rules did not significantly change any of the standards that are being used to judge the capability of decision rules.



**Figure 4-35** Box-plot for differences from paired t-test of average ambulance wait time



**Figure 4-36** Box-plot of differences from paired t-test of average percent coverage



**Figure 4-37** Box-plot of differences from paired t-test of average percent of time that percent coverage is less than 50%

### *Conclusions about Decision Rules*

The request and release rules that are selected play a significant role in determining how the system will operate. Simulating various decision rules can assist disaster planners in determining what their policy should be for requesting and releasing ambulances. Changing the

release rule did not have a significant impact on the system. None of the statistics that were being evaluated were found to be significantly different for any of the release rules tested.

Decision rules that prevent outside districts from sending additional ambulances if they have already sent 50% or more of their ambulances decrease the risk that is taken on by the outside ambulances. This is seen through an increase in the overall average percent coverage and by a decrease in the percent of time that the coverage is less than 50%. While this decision is good for the outside districts, those who are at the disaster scene find it less desirable. Implementing this policy increases the amount of time that victims must wait for an ambulance.

Only a small number of replications were run for each of the configurations of the system, and the system is limited by many assumptions, so the output should not be considered proof that one of the decision rules is always superior to the others. What this exercise did show is that the decision rules that are selected by Disaster planners are critical to how the system will perform. Some decision rules have a larger effect on the system than others. The effect of the decision rule is not always intuitive. Often one may consider the main effect that is the reason that they are implementing the rule, but they do not consider all of the side-effects that may come along with it. This is where the value of discrete-event simulation lies. It allows for the decision rules to be implemented into the system so that the overall impact can be seen.

## CHAPTER 5 - Conclusions

Discrete-event simulation should become a very powerful and effective tool within emergency preparedness and disaster planning. Most disaster response plans are never used and the physical simulations of them are good practice for those involved by are not a good tool for assessing the capability of the response system. Computer simulations allow the disaster response plan to be run under different scenarios and determine how effective the current plan is at responding to different levels of disasters. It allows for various decision rules and policies to be tested out to see what their overall impact on the system will be. Due to the many factors that contribute to the performance of the system, it is often hard to accurately guess how the system will respond to a given change. Simulating the system takes away much of that guess work and would allow disaster planners to see the effect of changing the system.

While simulation can be a powerful tool, the output of the simulation is only good if it is a close model to reality. The underlying assumptions of the simulation and the numbers and values that are used as input are critical in ensuring that the output from the simulation is in-fact a representation of what would likely happen in reality. A sensitivity analysis was performed to determine how much of an affect the values of certain variables have on the performance of the system. It was found that the values of *Volunteer Injury Rate*, *Injury Severity*, *Information Dissemination Rate*, and *Transportation Decision* all have a significant impact on at least one of the output statistics. *Volunteer Injury Rate* directly affects the demand for ambulances and thus has a significant impact on the Total Ambulance Time, Ambulance Wait Time, and Time to arrival at hospital. *Injury Severity* affects the number of victims that will be transported in a single ambulance and the time at which victims will begin seeking medical help. This has a significant impact on the Ambulance Wait Time and Total Ambulance Time statistics. *Information Dissemination Rate* affects the number of people who will choose ambulance transportation, which affects the demand for ambulances. This has a significant impact on the amount of time that a victim spends waiting for an ambulance, as reported in the Ambulance Wait Time statistic. The value of the Transportation Decision variable affects the demand for ambulance assistance and has an impact on the Total Ambulance Time, Ambulance Wait Time and Time to hospital statistics. The model is sensitive to changes in the values of the variables.

Improving the accuracy of the variable values in this model by capturing more real-life, historical data would improve the simulations ability to accurately simulate what would actually occur.

Even with limited data, the simulation created for this paper appears to do a satisfactory job of aligning with reality. The model was run with the input data from the tornado disaster that hit Greensburg, KS in May of 2007. The output of the simulation matched what occurred for nearly all of the statistics that were known. The time of the first arrival of a patient at the hospital, the time of the last arrival of a patient at the hospital, the total number of injuries sustained, the number of deaths, the number of Level 2 and Level 3 injuries, and the number of ambulances needed were all accurately predicted by the simulation model. The only statistic that was not accurately predicted was the number of Level 1 injuries. A 95% confidence interval for the number of Level 1 injuries created by the output of simulation was 60-71 victims. The actual value from the Greensburg tornado was 72. If the confidence level were dropped to 90%, then this statistic would also align with the actual events. All of the other statistics output by the simulation matched nicely with what occurred in Greensburg (See section 4.3).

In Section 4.4 it was shown that this simulation can be used to test how the system will perform with various decision rules. Only a small number of replications were run for each of the configurations of the system, and the system is limited by many assumptions, so the output should not be considered proof that one of the decision rules is always superior to the others. What this exercise did show is that the decision rules that are selected by Disaster planners are critical to how the system will perform. Some decision rules have a larger effect on the system than others. The effect of the decision rule is not always intuitive. Often one may consider the main effect that is the reason that they are implementing the rule, but they do not consider all of the side-effects that may come along with it. This is where the value of discrete-event simulation lies. It allows for the decision rules to be implemented into the system so that the overall affect can be seen.

In the future, discrete-event simulations could become a tool that is found in the toolboxes of disaster planners everywhere. The model described in this paper could be expanded to include the ability to simulate different kinds of disasters, not just tornado disasters. More scenarios could be considered, such as which emergency resources are destroyed by the disaster,

how much of the communication network is left in-tact, and what if the surrounding counties and ambulance districts are also being face with a disaster situation?

This same idea of looking at the capability of the ambulance response in providing timely care to tornado victims while minimizing the burden or risk that is put on surrounding districts could have many other applications. The most obvious is ambulance response to other types of disasters such as terrorist attacks, plane crashes or earthquakes. It could also be applied to other emergency response efforts such as the Fire Department response to forest fires.

A military war application could exist to simulate special missions that require pulling troops from many areas to help. If a war campaign pulls all of the troops from surrounding areas to complete the mission, the areas that the troops left are under covered and they are at a much higher risk.

In the utility industry, this same idea could be used to simulate the response of lineman to downed wires due to an ice storm, tornado, or hurricane. Linemen may be pulled from many states to aid in the efforts of restoring power, but they leave their home region uncovered should repairs be needed there.

## **5.1 Improvements**

There are many improvements that could be made to this model. Many assumptions are made, which may or may not line up with the actual protocol and procedures of a given areas disaster response plan. Many of the inputs and values of variables that are used in the model are unsupported or under supported.

### ***Model Inputs and Variable Values***

Improving the numbers in the model will increase its validity and its ability to be used as a decision making tool. Currently there are very few statistics available about medical emergency response or disaster response. This is due to two things. First, statistics are not always collected, especially in disaster situations. For example, in the Greensburg tornado, no data was collected about whether a person arrived via ambulance or other means. The hospitals focus was on providing medical care as quickly as possible, and thus data collection was not considered. This is not a problem unique to Greensburg or Pratt Regional Medical Center, Robin Blair discusses this problem in her article *Disaster-Proof Patients* (2007). She says, “During any mass casualty episode, be it a terrorist attach, pandemic event or a natural disaster, we have an enormous

problem keeping track of what we do to and with patients.” She goes on to say that a large source of this problem is that much of the record keeping has to be done manually with no continuity of record keeping. Such a problem would be magnified in rural communities where the adoption of technology is generally well-behind that of their metropolitan counter parts.

When data is collected, the information collected and the methods of reporting it seem to vary greatly. This makes it difficult to compile data from numerous sources. Finally, much of the data that is collected by the medical industry is not released. Confidentiality is critical to the medical industry and they often do not have the time, resources, or willingness to clean-up the data and remove confidential information so that the data can be released. Until more data is made available by the medical industry, it will be difficult to make a significant contribution to improving their systems.

### ***General Model***

The precision and accuracy of the model can be improved by using more regions. The more regions that the disaster area is divided into, the more accurate the travel times will be. Doing this will add to the complexity of initializing the system because it will require more values for Percent Destruction to be input, which means more decisions for the user about what values to set them at. Dividing the out of district ambulances into more regions will also improve the accuracy of their travel time as well as the percent coverage statistics.

### ***Decision Rules***

Increasing the number of replications that are run for evaluating various decision rules would improve the ability to distinguish the differences that each rule causes to the system. For the scope of this project, a small number of replications (5) were thought to be appropriate as the goal was simply to demonstrate the simulations ability as a decision tool, not to prove that a specific rule should be adopted into an emergency response plan. If decisions are going to be made from the simulation output, running five replications may not be sufficient.

## **5.2 Areas for Future Research**

Further research should be done into methods of data collection within the emergency and disaster response arena. Standardized methods for what type of data is collected should be

established. Easy, non-time consuming collection of this data is important, as time is critical to emergency response and if collecting data takes time away from the patients, then it is unlikely that hospitals, ambulance districts, or medical personnel will cooperate. Also, a method of cleaning-up medical data that is not time consuming and does not require a great deal of computer ability may make obtaining data from the medical industry easier.

The simulation could be expanded to take into consideration the effects of population and geographic parameters such as the average age of the population, the type of houses that are in the area, the climate of the region, and other factors. There are many factors that may have a significant impact on the likelihood of a person being injured. Research into the relationship between the type of dwelling that a person is in and their likelihood of injury has been researched by Bohonos (1999), but the results of this research have not been incorporated into the planning of medical response. These same factors may also play a role into the decision that a victim makes on how to reach the hospital.

The purpose of the triage station is to provide first-aid care to patients at the scene of the disaster so that they do not have to wait to be transported to the hospital. If the triage location is very close to the hospital, then its usefulness decreases. Research into the distance between the location of the disaster and hospitals and at what distances the triage location is beneficial could have a strong impact on disaster response planning.



## Bibliography

"NWS: Muhlenberg County, Ky., Tornado was 325 Yards Wide, Went 12 Miles." *Evansville Courier and Press*, February 7, 2008, 2008, sec. Local News (accessed February 8, 2008).

*Local Emergency Operations Plan for Riley County*. E-Fm Consulting, LLC, 2007.

Region III EMS-South Central Kansas. <http://www.regioniiiems.com/>

Ablah, Elizabeth, Annie M. Tinius, Kurt Konda, and Carolyn Synovitz. "Regional Health System Response to the 2007 Greensburg, Kansas, EF5 Tornado." *Disaster Medicine and Public Health Preparedness* 1, no. 2 (2007): 90-95.

Arboleda, Carlos A., Dulcy M. Abraham, and Robert Lubitz. "Simulation as a Tool to Assess the Vulnerability of the Operation of a Health Care Facility." *Journal of Performance of Constructed Facilities* 21, no. 4 (July/August, 2007): 302-312.

Auf der Heide, E. "The Importance of Evidence-Based Disaster Planning." *Annals of Emergency Medicine* 47, no. 1 (Jan, 2006): 34-49.

Balluz, Lina, Laura Schieve, Talmage Holmes, Stephanie Kiezak, and Josephine Malilay. "Predictors for People's Response to a Tornado Warning: Arkansas, 1 March 1997." *Disasters* 24, no. 1 (2000): 71-77.

Birk, H. O. and L. O. Henriksen. "Prehospital Interventions: On-Scene-Time and Ambulance-Technicians' Experience." *Prehospital and Disaster Medicine : The Official Journal of the National Association of EMS Physicians and the World Association for Emergency and Disaster Medicine in Association with the Acute Care Foundation* 17, no. 3 (Jul-Sep, 2002): 167-169.

Blair, R. "Disaster-Proof Patients." *Health Management Technology* 28, no. 2 (Feb, 2007): 44, 46-7.

Bohonos, J. J. and D. E. Hogan. "The Medical Impact of Tornadoes in North America." *The Journal of Emergency Medicine* 17, no. 1 (Jan-Feb, 1999): 67-73.

- Breakey, P. "Emergency Nursing during the Edmonton Tornado." *The Canadian Nurse* 84, no. 8 (Sep, 1988): 36-38.
- Brown, L. H., E. B. Lerner, B. Larmon, T. LeGassick, and M. Taigman. "Are EMS Call Volume Predictions Based on Demand Pattern Analysis Accurate?" *Prehospital Emergency Care : Official Journal of the National Association of EMS Physicians and the National Association of State EMS Directors* 11, no. 2 (Apr-Jun, 2007): 199-203.
- Cadigan, R. T. and C. E. Bugarin. "Predicting Demand for Emergency Ambulance Service." *Annals of Emergency Medicine* 18, no. 6 (Jun, 1989): 618-621.
- Centers for Disease Control (CDC). "Tornado Disaster--Kansas, 1991." *MMWR.Morbidity and Mortality Weekly Report* 41, no. 10 (Mar 13, 1992): 181-183.
- Centers for Disease Control (CDC). "Tornado Disaster--Illinois, 1990." *MMWR.Morbidity and Mortality Weekly Report* 40, no. 2 (Jan 18, 1991): 33-36.
- Centers for Disease Control (CDC). "Tornado Disaster--Texas." *MMWR.Morbidity and Mortality Weekly Report* 37, no. 30 (Aug 5, 1988): 454-6, 461.
- Centers for Disease Control and Prevention (CDC). "Tornado Disaster -- Texas, may 1997." *MMWR.Morbidity and Mortality Weekly Report* 46, no. 45 (Nov 14, 1997): 1069-1073.
- Centers for Disease Control and Prevention (CDC). "Tornado-Associated Fatalities--Arkansas, 1997." *MMWR.Morbidity and Mortality Weekly Report* 46, no. 19 (May 16, 1997): 412-416.
- Daley, W. R., S. Brown, P. Archer, E. Kruger, F. Jordan, D. Batts, and S. Mallonee. "Risk of Tornado-Related Death and Injury in Oklahoma, May 3, 1999." *American Journal of Epidemiology* 161, no. 12 (Jun 15, 2005): 1144-1150.
- Eckstein, M., L. Chan, A. Schneir, and R. Palmer. "Effect of Prehospital Advanced Life Support on Outcomes of Major Trauma Patients." *The Journal of Trauma* 48, no. 4 (Apr, 2000): 643-648.
- Freese, J., N. J. Richmond, R. A. Silverman, J. Braun, B. J. Kaufman, and J. Clair. "Impact of a Citywide Blackout on an Urban Emergency Medical Services System." *Prehospital and Disaster Medicine : The Official Journal of the National Association of EMS Physicians and the World Association for Emergency and Disaster Medicine in Association with the Acute Care Foundation* 21, no. 6 (Nov-Dec, 2006): 372-378.

- Glass, R. I., R. B. Craven, D. J. Bregman, B. J. Stoll, N. Horowitz, P. Kerndt, and J. Winkle. "Injuries from the Wichita Falls Tornado: Implications for Prevention." *Science* 207, no. 4432 (Feb 15, 1980): 734-738.
- Goldberg, Jeffrey B. MS, PhD. "Operations Research Models for the Deployment of Emergency Services Vehicles." *EMS Management Journal* 1, no. 1 (2004): 20-39.
- Golec, Judith A. and Patrick J. Gurney. *Preliminary Paper #34: The Problem of Needs Assessment in the Delivery of EMS* Disaster Research Center, 1977.
- Gong, Qiang and Rajan Batta. "Allocation and Reallocation of Ambulances to Casualty Clusters in a Disaster Relief Operation." *IIE Transactions* 39, no. 1 (2007): 27-39.
- Green III, Walter G. "Mass Casualty Incident Management: The Virginia Model." Paper Presented at the 2000 National Disaster Medical System Conference, .
- Greenway, Jerry. "14 Confirmed Dead in Macon County Tornadoes." *Macon County Times*, February 7, 2008, 2008 (accessed February 8, 2008).
- Grossman, D. C., A. Kim, S. C. Macdonald, P. Klein, M. K. Copass, and R. V. Maier. "Urban-Rural Differences in Prehospital Care of Major Trauma." *The Journal of Trauma* 42, no. 4 (Apr, 1997): 723-729.
- Harris, Pat. "Death Toll Rises to 57 in U.S. Tornadoes." *Reuters*, February 8, 2008, 2008 (accessed February 8, 2008).
- Jia, Hongzhong, Fernando Ordonnez, and Maged Dessouky. "A Modeling Framework for Facility Location of Medical Services for Large-Scale Emergencies." *IIE Transactions* 39, no. 1 (2007): 41-55.
- Kenning, Chris. "Death and Devastation." *Courier-Journal.Com*, February 7, 2008, 2008 (accessed February 8, 2008).
- Mandelbaum, I., D. Nahrwold, and D. W. Boyer. "Management of Tornado Casualties." *The Journal of Trauma* 6, no. 3 (May, 1966): 353-361.
- Marr, J. "Kalamazoo Medics Say 'Fantastic!' to Health Personnel Response After Tornadoes." *Michigan Medicine* 79, no. 20 (Jul, 1980): 374-376.

- May, A. K., G. McGwin Jr, L. J. Lancaster, W. Hardin, A. J. Taylor, S. Holden, G. G. Davis, and L. W. Rue 3rd. "The April 8, 1998 Tornado: Assessment of the Trauma System Response and the Resulting Injuries." *The Journal of Trauma* 48, no. 4 (Apr, 2000): 666-672.
- May, B. M., D. E. Hogan, and K. R. Feighner. "Impact of a Tornado on a Community Hospital." *The Journal of the American Osteopathic Association* 102, no. 4 (Apr, 2002): 225-228.
- McCain, Courtney. New Direction for Rural Survivability. *JEMS.Com*, July 26, 2007. , [http://www.jems.com/news\\_and\\_articles/articles/New\\_Direction\\_for\\_Rural\\_Survivability.html](http://www.jems.com/news_and_articles/articles/New_Direction_for_Rural_Survivability.html) (accessed 1/28/2008).
- Morrisey, M. A., R. L. Ohsfeldt, V. Johnson, and R. Treat. "Trauma Patients: An Analysis of Rural Ambulance Trip Reports." *The Journal of Trauma* 41, no. 4 (Oct, 1996): 741-746.
- Naser, R. O., Jr and W. A. Cole Jr. "3 April 1974--Tornado." *The Journal of the Kentucky Medical Association* 72, no. 6 (Jun, 1974): 319-321.
- Noji, E. K. "Disaster Epidemiology." *Emergency Medicine Clinics of North America* 14, no. 2 (May, 1996): 289-300.
- NYC Fire Department. "FDNY Vital Statistics." New York City Fire Department. [http://nyc.gov/html/fdny/pdf/vital\\_stats\\_2007\\_final.pdf](http://nyc.gov/html/fdny/pdf/vital_stats_2007_final.pdf) (accessed 2/25, 2008).
- Potter, Tim. "Greensburg Residents Held Tight as Neighbors, Rescuers Searched, Helped." *The Wichita Eagle*, May 27, 2007, 2007 (accessed January 17, 2008).
- Prilliman, K., G. Solis, M. Swartz, and K. Conley. "Disaster Response: A Review of the April 26, 1991, Kansas Tornado." *Journal of Emergency Nursing: JEN : Official Publication of the Emergency Department Nurses Association* 19, no. 3 (Jun, 1993): 209-211.
- Repede, John F. "Developing and Validating a Decision Support System for Locating Emergency Medical Vehicles in Louisville, Kentucky." *European Journal of Operations Research* 75, no. 3 (1994): 567-581.
- Siler, K. F. "Predicting Demand for Publicly Dispatched Ambulances in a Metropolitan Area." *Health Services Research* 10, no. 3 (Fall, 1975): 254-263.
- Smeed, R.J., and Jeffcoate, G.O. "The variability of car journey times on a particular route." *Traffic Engineering Control* 13, no 6 (Oct, 1971): 238-243.

- Sookram, S., H. Borkent, G. Powell, W. D. Hogarth, and L. Shepherd. "Tornado at Pine Lake, Alberta - Assessment of the Emergency Medicine Response to a Disaster." *CJEM : Canadian Journal of Emergency Medical Care = JCMU : Journal Canadien De Soins Medicaux d'Urgence* 3, no. 1 (Jan, 2001): 34-37.
- Stout, J. L. "System Status Management. the Strategy of Ambulance Placement." *JEMS : A Journal of Emergency Medical Services* 8, no. 5 (May, 1983): 22-32.
- Stripe, S. C. and J. Susman. "A Rural-Urban Comparison of Prehospital Emergency Medical Services in Nebraska." *The Journal of the American Board of Family Practice / American Board of Family Practice* 4, no. 5 (Sep-Oct, 1991): 313-318.
- Toregas, Constantine, Ralph Swain, Charles ReVelle, and Lawrence Bergman. "The Location of Emergency Service Facilities." *Operations Research* 19, no. 6 (October 1971, 1971): 1363-1373.
- United States Department of Agriculture (USDA). "Measuring Rurality: What is Rural?" USDA Economic Research Service. <http://www.ers.usda.gov/Briefing/Rurality/WhatisRural/> (accessed 2/22, 2007).

## Appendix A - Calculations for Tornado Destruction Percentages

**Table 5-1 Summary of Percent Destruction statistics**

<b>Tornado</b>	<b>% Destruction</b>	<b>% injured/killed</b>
Wichita Falls	62.5	0.57
Texas 87	85	2.97
Greensburg, KS	95	6.80
Henderson, KY	64.29	0.81
Andover, 91	84	2.8

Kansas, 1991—CDC reports that more than 8000 people required disaster-relief services (assume 8000 people directly in the path of the storm). Over 200 injuries and 24 deaths (assume 224 dead/injured). This means that 2.8% of the people in the path of the storm were injured/killed. CDC reports that 205 out of 244 of the homes in a mobile home park were destroyed, thus we will assume an 84% destruction rate.

Wichita Falls, 1979—Glass, et al reports that 3000 of the 4800 homes were either completely destroyed or rendered uninhabitable (62.5%). They later report that the estimated total population of the tornado zone was 18,043 people. Of these 102 were fatally or seriously injured. Giving a percent injured of 0.565%

Texas, 1987—CDC reports that Saragosa was a Hispanic community of approximately 5,415 people. 30 people were killed and 131 injured. Giving a percent of injured/killed of 2.97%. [www.stormtrack.org/library/1987/saragosa.htm](http://www.stormtrack.org/library/1987/saragosa.htm) reports that 85% of the town was destroyed.

Greensburg, 2007—Ablah, et al (2007) reports that 95% of the homes and businesses in Greensburg were destroyed. It also reports that there were 12 deaths and 90 people who were treated in hospitals. It reports that the population of the Greensburg area at the time of the disaster was 1500 people. This means 6.8% of the people were injured or killed.

Henderson, KY—Fox News (<http://www.foxnews.com/story/0,2933,174687,00.html>) reported that 22 were killed and 200 injured in the tornado that struck Henderson, KY on November 6, 2005. 225 of the 300 homes in a trailer park were destroyed or severely damaged, giving a destruction rate of 64.24%. According to the 2000 census data, the population of Henderson, KY was 27,373. This makes the injury/death rate 0.81%.