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An Index To Measure Efficiency Of Hospital Networks For Mass Casualty Disasters

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AN INDEX TO MEASURE EFFICIENCY OF HOSPITAL NETWORKS FOR MASS CASUALTY DISASTERS

by

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ABSTRACT

Disaster events have emphasized the importance of healthcare response activities due to the large number of victims. For instance, Hurricane Katrina in New Orleans, in 2005, and the terrorist attacks in New York City and Washington, D.C., on September 11, 2001, left thousands of wounded people. In those disasters, although hospitals had disaster plans established for more than a decade, their plans were not efficient enough to handle the chaos produced by the hurricane and terrorist attacks. Thus, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) suggested collaborative planning among hospitals that provide services to a contiguous geographic area during mass casualty disasters. However, the JCAHO does not specify a methodology to determine which hospitals should be included into these cooperative plans. As a result, the problem of selecting the right hospitals to include in exercises and drills at the county level is a common topic in the current preparedness stages.

This study proposes an efficiency index to determine the efficient response of cooperative-networks among hospitals before an occurrence of mass casualty disaster. The index built in this research combines operations research techniques, and the prediction of this index used statistical analysis. The consecutive application of three different techniques: network optimization, data envelopment analysis (DEA), and regression analysis allowed to obtain a regression equation to predict efficiency in predefined hospital networks for mass casualty disasters. In order to apply the proposed methodology for creating an efficiency index, we selected the Orlando area, and we defined three disaster sizes.

Then, we designed networks considering two perspectives, hub-hospital and hub-disaster networks. In both optimization network models the objective function pursued to: reduce the

travel distance and the emergency department (ED) waiting time in hospitals, increase the number of services offered by hospitals in the network, and offer specialized assistance to children. The hospital network optimization generated information for 75 hospital networks in Orlando.

The DEA analyzed these 75 hospital networks, or decision making units (DMU's), to estimate their comparative efficiency. Two DEAs were performed in this study. As an output variable for each DMU, the DEA-1 considered the number of survivors allocated in less than a 40 miles range. As the input variables, the DEA-1 included: (i) The number of beds available in the network; (ii) The number of hospitals available in the network; and (iii) The number of services offered by hospitals in the network. This DEA-1 allowed the assignment of an efficiency value to each of the 75 hospital networks. As output variables for each DMU, the DEA-2 considered the number of survivors allocated in less than a 40 miles range and an index for ED waiting time in the network. The input variables included in DEA-2 are (i) The number of beds available in the network; (ii) The number of hospitals available in the network; and (iii) The number of services offered by hospitals in the network. These DEA allowed the assignment of an efficiency value to each of the 75 hospital networks. This efficiency index should allow emergency planners and hospital managers to assess which hospitals should be associated in a cooperative network in order to transfer survivors. Furthermore, JCAHO could use this index to evaluate the cooperating emergency hospitals' plans.

However, DEA is a complex methodology that requires significant data gathering and handling. Thus, we studied whether a simpler regression analysis would substantially yield the same results. DEA-1 can be predicted using two regression analyses, which concluded that the average distances between hospitals and the disaster locations, and the size of the disaster explain the efficiency of the hospital network. DEA-2 can be predicted using three regressions, which included size of the disaster, number of hospitals, average distance, and average ED waiting time, as predictors of hospital network efficiency. The models generated for DEA-1 and DEA-2 had a mean absolute percent error (MAPE) around 10%. Thus, the indexes developed through the regression analysis make easier the estimation of the efficiency in predefined hospital networks, generating suitable predictors of the efficiency as determined by the DEA analysis. In conclusion, network optimization, DEA, and regressions analyses can be combined to create an index of efficiency to measure the performance of predefined-hospital networks in a mass casualty disaster, validating the hypothesis of this research.

Although the methodology can be applied to any county or city, the regressions proposed for predicting the efficiency of hospital network estimated by DEA can be applied only if the city studied has the same characteristics of the Orlando area. These conditions include the following: (i) networks must have a rate of services lager than 0.76; (ii) the number of survivors must be less than 47% of the bed capacity EDs of the area studied; (iii) all hospitals in the network must have ED and they must be located in less than 48 miles range from the disaster sites, and (iv) EDs should not have more than 60 minutes of waiting time.

The proposed methodology, in special the efficiency index, support the operational objectives of the 2012 ESF#8 for Florida State to handle risk and response capabilities conducting and participating in training and exercises to test and improve plans and procedures in the health response.

To my lovely parents, Teresa Torres and Celedonio Bull.

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LIST OF ACRONYMS/ABBREVIATIONS

A&E	Accident and Emergency Department
AHRQ	Agency for Healthcare Research and Quality
DEA	Data Envelopment Analysis
DOM	Disaster Operations Management
ED	Emergency Department
EMS	Emergency Medical Service
ESAR-VHP	Emergency System for Advance Registration of Volunteer Health Care Personnel
ESF	Emergency Support Function annexes
FEMA	Federal Emergency Management Agency
GAO	U.S. Government Accountability Office
GIS	Geographic Information System
HHS	Department of Health and Human Services
HPP	Hospital Preparedness Program
IAP	Incident Action Plan
ICS	Incident Command System
JCAHO	Joint Commission on Accreditation of Healthcare Organizations
N°	Number of
NRF	National Response Framework
NRP	National Response Plan
OR/MS	Operation Research and Management Science

PAHO	Pan American Health Organization
SDO	Strong Disposability of Outputs
SFA	Stochastic Frontier Analysis
USDHS	US Department of Homeland Security
WDO	Weak Disposability of Outputs
WHO	World Health Organization

CHAPTER ONE: INTRODUCTION

During the last decades, disaster events producing a large number of victims have emphasized the importance of healthcare response activities in the disaster management field. Some of the most important disasters in the United States are the Hurricane Katrina in New Orleans in 2005, and the terrorist attacks in New York City and Washington, D.C. on September 11, 2001. In these cases, although most of the hospitals had already settled disaster plans for more than a decade, their response plans did not work efficiently to handle the chaos produced by the hurricane and the terrorist attacks. It is clear that government agencies and private-sector efforts have been insufficient to improve the hospital response to a catastrophic event (Auf Der Heide, 2006; Auf Der Heide, 1996; Farmer and Carlton, 2006; Schultz, Koening, and Noji, 1996). For that reason, the dissertation focuses on disasters in the United States, applying the proposed methodology in the Orlando area.

Eight sections form this chapter, which are detailed as follows. The definitions and categorizations of disasters are given in sections 1 and 2 respectively. A brief description of emergency management is presented in Section 3. The following four sections describe the problem statement, the scope of the research and hypothesis, the significance of this study, and the contributions of the research correspondingly. The last section presents the outline of this document.

1.1 Definition of Disasters

Although there are different disaster definitions based on audience, historical events, and field of study, most of them agree on defining a disaster as a situation that cannot be managed with conventional or standard procedures (Canton, 2007; Butler *et al*., 2007; Comfort, 2007; Perry, 2007; McEntire, 2007; Federal Emergency Management Agency, [FEMA], 2010). The FEMA defines incident[1] as

"An occurrence or event natural or human-caused that requires an emergency response to protect life or property. Incidents can, for example, include major disasters, emergencies, terrorist attacks, terrorist threats, wildland and urban fires, floods, hazardous materials spills, nuclear accidents, aircraft accidents, earthquakes, hurricanes, tornadoes, tropical storms, war-related disasters, public health and medical emergencies, and other occurrences requiring an emergency response"(FEMA Glossary, 2010).

The World Health Organization (WHO) defines a mass casualty incident as "... an event which generates more patients at one time than locally available resources can manage using routine procedures" (McArdle, 2007, p.9). In addition to the WHO definition of a mass casualty incident, the Pan American Health Organization (PAHO) defines mass casualty incident as "... Any event resulting in a number of victims large enough to disrupt the normal course of emergency and health care services" (Bordonado *et al*., 2001, p.3). From an emergency medicine perspective, Antosia (2006, p. 3) states that a "... disaster is when the number of patients presenting within a given period are such that the emergency department cannot provide care for

[1] Disaster and incident is considered synonymous.

them without assistance." He also claims that each disaster is unique based on social, economic, and health baseline features of the affected area.

In addition, Burkle and Greenough (2008) identify seven factors that transform a disaster in a public health emergency, i.e. a mass casualty disaster. These factors are (1) lack of the public health infrastructure in developing countries, (2) deficient capacity of health infrastructure system to response to a crisis; (3) destruction of public health capacity during the disaster; (4) geographically extension of the disaster, (5) population size, distribution, and density; (6) prolonged exposure of the disaster (7) Conditions of the environment after the disaster.

Thus, these definitions agree that mass casualty disasters are events that harm a large number of people, causing a significant number of victims, which number is often higher than the capacity of the emergency and health care services located in the area of the incident. Even though Antosia (2006) proposes that each disaster is unique; however, we consider that mass casualty disasters can be generalized in this research.

1.2 Categorization of Disasters

Berren, Beigel, and Gherther (1980) classify a disaster following a typology oriented to predict the psychological impact based on five categories. These categories include: (i) type of disaster (natural or man-made), (ii) duration of disaster (short or long duration), (iii) degree of personal impact (high or low personal impact), (iv) potential for occurrence (high or low potential), and (v) control over future impact (high or low control). In 1990, Boer develops a methodology, the disaster severity scale, to categorize a mass casualty disaster. This scale has seven aspects: (i) the effect on the surrounding community; (ii) the cause; (iii) the duration of the cause of disaster; (iv) the radius of the disaster area; (v) the number of casualties; (vi) the nature of the injuries and distribution by level of injured survivors; and (vii) the time required by the rescue organizations. In order to calculate the severity of a disaster, this author classifies each disaster according to each category, and takes the value associated with each level into the category, and then, all the values assigned to each category are added. The maximum value of severity in this scale is 13 and the minimum value is 1.

To explain Table 1, Hurricane Katrina is used as an example. For this disaster, Category 1 presents a level of compound disaster equal to a value of two. For Category 2, the level is natural with a value of one. In Category 3, its value is one. For Category 4, the level is large, equivalent to a value equal to two, Category 5 is equal to value two, Category 6 is equal to value one, and finally, Category 7 is equal to value two. Then, it is possible to estimate that Katrina's level of severity, in the Boer's scale by adding all the categories' values, is a level 12.

Table 1: Disaster Severity Scale Based on Boer (1990)

N^o	Category	Levels	Values	Example
1	Effect on the surrounding community	Simple Disaster	1	Traffic accident
		Compound Disaster	2	Earthquake
2	Cause	Man-Made	0	Traffic accidents
		Natural	1	Tsunami
3	Duration of the cause of disaster	Short (less than 1 hour)	0	Traffic Accident
		Relatively long (1 -24 hours)	1	Hurricanes
		Long (more than 24 hours)	2	Epidemics
4	Radius of the disaster area	Small (less than 1 km.)	0	Traffic accident
		Relatively large (1-10 km.)	1	Hurricane
		Large (more than 10 km.)	2	Earthquake
5	Number of casualties	Minor (25 -100 casualties alive or dead, or 10-50 casualties requiring admission to hospital)	0	Traffic accident
		Moderate (100-500 casualties alive or dead, or 50 -250 casualties requiring admission to hospital)	1	Poisonous food
		Major (more than 500 casualties alive or dead, or more than 250 casualties requiring admission to hospital)	2	Epidemic
6	Nature of the injuries sustained by living victims	Serious (normal = 10 %;) Moderate (normal = 30%) Light (more than 60%)	0	Traffic accident
		Serious (normal = 10 %;) Moderate (normal = 30%) Light (normal = 60%)	1	Fire
		Serious (more than 10 %;) Moderate (normal = 30%) Light (normal = 60%)	2	Plane crash
7	Time requested by the rescue organization for primary treatment	Short (less than 6 hour)	0	Traffic accident
		Relatively long (6 -24 hours)	1	Terrorist attack
		Long (more than 24 hours)	2	Earthquake

The American College of Emergency Physicians suggests an alternative disaster classification for mass casualties' incidents based on three levels (Stone and Humphries, 2007, p. 30):

"Level 1— a localized multiple casualty emergency wherein local medical resources are available and adequate to provide for triage[2], field medical treatment, and stabilization. The

[2] Triage is the sorting of and allocation of treatment to patients and especially battle and disaster victims according to a system of priorities designed to maximize the number of survivors. Source: http://www.merriam-webster.com/dictionary/triage (accessed on October1, 2012)

patients will be transported to the appropriate local medical facility for further diagnosis and treatment.

Level 2— a multiple casualty emergency in which the large number of casualties or lack of local medical care facilities are such as to require multijurisdictional (regional) medical mutual aid.

Level 3— a mass casualty emergency wherein local and regional medical resource capabilities are exceeded or overwhelmed. Deficiencies in medical supplies and personnel are such as to require assistance from state or federal agencies.”

In brief, both the public health capacities at a defined geographical area and the intensity of the disaster are the foundation to classify a mass casualty disaster. However, it is important to mention that the authors do not include the proportion of the victims based on the total population settled in the affected area.

1.3 Emergency Management

This section discusses the current U.S. emergency management framework for mass casualties and the public health emergency management aspects.

1.3.1 U.S. Emergency Management

From a government perspective, the United States’s emergency response operates under a Federal system (McEntire and Dawson, 2007), which is led by the U.S. Department of Homeland Security. One of the three major goals of the National Strategy for Homeland Security seeks to reinforce the U.S. emergency management policies. This goal is to "respond to and recover from incidents that do occur" (U.S. Department of Homeland Security [USDHS], 2008). After Hurricane Katrina hit New Orleans, the Federal Government agencies created the National Response Framework (NRF), which replaces the former National Response Plan (NRP). The NRF guides how the national institutions conduct all-hazards response, and it also states the coordination and identification of responsible personnel and its role among communities, state governments, the Federal government, private-sector organizations, and nongovernmental institutions (USDHS, 2008). The NRF has 15 Emergency Support Function (ESF) annexes. These annexes arrange Federal resources and capabilities into the most needed functional areas of the national response. The ESF #8[3] is the only annex related to the Public Health and Medical Service. This annex is under the authority of the Department of Health and Human Services (HHS), and it establishes all procedures for response to public health emergencies (USDHS, 2008a). The State of Florida Final Draft Comprehensive Emergency Management Plan 2012 includes 18 ESF annexes. The 2012 ESF#8 for Florida State describes objectives, such as "... Maintain and implement the Florida Public Health and Healthcare Preparedness Strategic Plan to manage risk and build response capabilities [and] ... Conduct and participate in trainings and exercises to validate, test and improve plans and procedures" (The State of Florida Final Draft Comprehensive Emergency Management Plan, 2012, ESF 8 Appendix-, pp.1- 20).

The Incident Command System (ICS) is a standardized response incident management manual for all types of hazards. ICS works when more than one agency have jurisdiction over a zone or when incidents cross different political jurisdictions. ICS is a single incident action plan

[3] The Emergency Support Function Annexes for Florida State are available in the Florida Division of Emergency Management at http://floridadisaster.org/cemp.htm

to coordinate agencies work through the designated members of a unified command who establishes objectives and strategies. However, each agency maintains its own authority, responsibility, and accountability (USDHS, 2008b).

Mass casualty incidents frequently involve more than one organization due to the scale of the disaster. In this case, hospitals and other institutions have to implement the ICS and the Incident Action Plan (IAP). An important feature of implementing ICS is that it does not consider the administrative structure of the organization or hospital before an incident occurs. The IAP, on the other hand, pre-establishes the Incident Commander's responsibilities in each institution or hospital. The Incident Commander is responsible for assessing staff needs, establishing incident objectives, directing staff to develop the IAP, and overseeing all activities and functions until specific personnel take control of those activities (Barnett, 2010).

1.3.2 Public Health Emergency Management

The hospital preparedness for dealing with mass casualty disasters is not new. In 1961, Chesbro is the first author who proposed a hospital disaster plan. Lately, various authors have proposed several recommendations to develop hospital disaster plans. These recommendations include the following aspects: (i) identification of the types of disasters that occur frequently in the geographic area of interest (Auf Der Heide, 1996), (ii) incorporation of aspects related to multijurisdictional coordination, prevention, surveillance of disaster, warning, evacuation, and recovery (Auf Der Heide, 1996; Landesman, 2005), (iii) analysis of hospital integration into community emergency preparedness (Braun *et al.*, 2006). These recommendations may help hospitals develop a hospital emergency plan according to the public health model for disaster, which follows the comprehensive emergency management model established by FEMA.

In addition to the comprehensive emergency management model, hospitals should also follow the Environment of Care Standards of the Joint Commission on Accreditation of Healthcare Organizations (JCAHO). JCAHO's Environment of Care Standards suggests three conditions related to emergency management, which are the following:

i. Hospital capability to sustain itself between 72 to 96 hours after a disaster occurs. If the hospital does not have that capability, it has to create an emergency plan accordingly.

ii. Every health care organization must have an emergency management program in place.

iii. Each health care organization must have at least one exercise per year that includes an influx of volunteer or simulated patients to test the response emergency plan (Wiener, 2006).

In addition, drills or exercises have to be conducted at least four, but not more than eight months apart (Wiener, 2006). The Environment of Care Standards also requires hospitals to provide services to contiguous geographic areas, developing cooperative plans among health institutions (Hsu *et al*, 2004). To provide services to this type of areas, Cryer and Hiatt (2009) propose development of regional trauma networks for each state of the United States. This also improves the hospital disaster preparedness. Although most of the healthcare institutions agree on the importance of coalitions in dealing with any disaster situation, some senior hospital leaders are afraid of the liability of their institutions, after a catastrophic disaster occurs (Toner *et* *al*., 2009). Harris and Clements (2007, p. 494) point out the lack of guidelines to determine an effective public health emergency planning network, which made it difficult to accomplish the requirements of the Environment of Care Standards.

Courtney *et al*. (2009b) highlight the importance of balancing the available capacities of the hospitals in order to respond collectively to any catastrophe. The U.S. Department of Health and Human Services established the Hospital Preparedness Program (HPP) (Courtney *et al*., 2009b), which improved the hospital disaster preparedness in the last decade. However, Courtney, Toner, and Waldhorn (2009a) claim that the U.S. healthcare system is not prepared to respond to mass casualty disasters.

In addition, to managing hospitals' capacities using coalitions and planning, hospitals have to be prepared to deal with unexpected increases in the demand for their services, during and after a disaster. According to the Agency for Healthcare Research and Quality (AHRQ), surge capacity is the "ability to rapidly expand beyond normal services to meet the increased demand for qualified personnel, medical care, and public health in the event of bioterrorism or other large-scale public health emergencies or disasters" (AHRQ, 2004). Gougelet (2010) defines Medical Surge Capacity as "the ability to provide medical treatment to patients that exceed normal healthcare system capacity by more than 30%." The most important features of disaster surge capacity are: (1) the complex composition: staff, stuff, and structure; (2) the complexity to standardize and quantify disaster surge; and (3) the complexity of disaster surge compared to issues that are not associated with daily surge (Kaji, Koening and Bey, 2006).

However, the national daily surge capacity is not adequate for mass-casualty events (Katz, Staiti and McKenzie, 2006; Higgins, Wainright, Lu, and Carrico, 2004). DeLia and Wood

(2008) established that the surge capacity needed to deal with a mass casualty disaster is smaller in the East Coast than in the West Coast, due to the rapid population growth in the East Coast.

To create surge capacity in hospitals during a disaster, Kelen *et al*. (2009) use the reverse triage[4]. In order to improve the staff component of the disaster surge capacity, Schultz and Stratton (2007) propose creating a database with a region's health care providers and hospital-based credentialing. This approach should provide easier and faster access to medical staff contact-information than the Emergency System for Advance Registration of Volunteer Health Care Personnel (ESAR-VHP), which is state-based.

The emergency logistics plays a key role in the improvement of the hospital response in a mass casualty disaster. Van Vactor (2010) states that, although health care logisticians do not have contact with patients, their work impacts medical outcomes. It means that there is a direct relationship between the logistic and hospital performance. For example, the medical supplies are insufficient to treat survivors and the time to transport these victims is critical to save their lives.

A suitable emergency logistics[5] help the healthcare system during mass casualty disasters to resolve problems, such as allocation of medical resources, locations of healthcare units, and evacuation of injured survivors to hospitals. Some models for these location-allocation problems are linear and non-linear models (Earnshaw and Dennett, 2003; Jia, Ordóñez, and Dessouky, 2007a; Yi and Ozdamar, 2007; Balcik and Beamon, 2008), and heuristics and meta-heuristics

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[4] Early discharge of hospitalized patients at low risk.

[5] The emergency logistics is complex during mass casualty disaster. The reasons for this complexity include: a wide type of demanded products, urgent demand, lack of accurate information on relief demand, risks associated with adequate and timely delivery, lack of high quantity of resources, multiple point of distributions, and decentralized storage (Haghani and Oh, 1996; Zhu and Ji, 2009; Balcik and Beamon, 2008; Yi and Ozdamar, 2007; Cheng and Lu, 2008).

techniques (Jia, Ordonez and Dessouky, 2007 b; Ozdamar and Yi, 2008; Farahani, SteadieSeifi and Asgari, 2010).

The use of the Geographic Information Systems (GIS) has become widely common in solving location-allocation problems, complementing the emergency logistics approach (linear, non-linear, heuristics and meta-heuristics techniques). The spatial analysis through GIS helps managers to: allocate health resources closer of the community (McLafferty, 2003; Rafanelli *et al.*, 1995), assess ambulance response performance (Peters and Hall, 1999), and analysis of vulnerability to support hospital plans (Wood and Good, 2004; Nazir *et al.,* 2006; El Morjani *et al.*,2007).

The simulation techniques are other approaches to model hospital response in disasters. These techniques work on a large variety of problems in the healthcare system, improving emergency departments and operating rooms (see Jun *et al.*, 1999, for surveys on simulation in emergency departments). Jain and McLean (2006) classified four groups in modeling and simulation tools for emergency management, which are not mutually-exclusive: (1) Incident Impact Modeling Tools, (2) Emergency Response Planning Tools, (3) Tools for Incident Management Training, and (4) Tools for Identification and Detection. Some specific applications of simulation techniques include: the balance of ambulance availability during mass gatherings (e.g.,Wu and Hwang, 2009), medical resource allocation after an earthquake (e.g., Fiedrich, 2007), training related to patient flow, security, and materials/resources (e.g., Hsu *et al.*, 2004; Fiedrich, 2007).

In addition, Altay and Green III (2006) develop a wide review of Operations Research and Management Science (OR/MS) applications for disaster operations management (DOM).

These authors identify that “DOM lacks widely accepted measures of productivity and efficiency” (Altay and Green III, 2006, p. 483).

In summary, the following topics are critical to improve the hospital's emergency response in a mass casualty disaster: (i) Create models to improve surge capacity (beds, staff, and medical supplies); (ii) Improve the hospitals networks' coordination; (iii) Create methods combining GIS, simulation, and optimization for vulnerability analysis; and (iv) Create guidelines for determining an efficient emergency hospitals networks. Through this research, it is possible to offer an index to measure efficiency of hospital networks for mass casualty disasters, which can be part of the guidelines for determining an efficient public health emergency planning network.

1.4 Problem Statement

Hospital managers face difficulties to evaluate the efficiency of different hospital networks and emergency planning, especially due to the lack of performance measurements to evaluate the efficiency of hospital networks. Scholars have used different measure to evaluate efficiency in a set of hospitals. The most common approaches are stochastic frontier analysis, data envelopment analysis, and the Malmquist index. However, these approaches are not strong enough to estimate the efficiency for hospital network in mass casualty disasters because these analyses frequently include deterministic analysis, single institution, or single operation scenarios, which are not suitable for computing a global efficiency factor.

Network models offer a different approach, defining networks based on: Supply, demand, and capacity. Nevertheless, the network models proposed could not be compared based on standard parameters to define which network is more efficient among a set of networks. Some authors apply disaster operations management to evaluate emergency plans in hospitals. However, this approach does not offer a measure of productivity and efficiency to compare behaviors during disasters (Altay and Green III, 2006), and there is not a guideline for determining an efficient public health emergency planning network (Harris and Clements, 2007). From an American institutional perspective, even though JCAHO requires hospitals to provide services to a contiguous geographic area in cooperative plans, it does not have any performance measurement to evaluate how many hospitals work in a cooperative fashion to cover a specific area during a disaster.

Thus, this research proposes a study of hospital networks efficiency for mass casualty, identifying which variables affect the efficiency of those networks. It also develops an index that incorporates those variables in a mathematical model to obtain an efficiency index. Afterward, this index allows hospital managers to assess which hospitals should be associated in a cooperative network in order to transfer survivors, giving them appropriate treatment. In addition, institutions such as JCAHO can use the index to evaluate the hospitals' cooperative plans requested in JCAHO's new Environment of Care Standard.

1.5 Scope of Research and Hypothesis

The study of hospital network efficiency for mass casualty seeks to combine operations research and forecasting to obtain an efficiency measurement function for any hospital network. The combination of these two approaches is possible by the consecutive application of three different techniques: network optimization, data envelopment analysis (DEA), and regression analysis. The network optimization technique allows the analysis of networks according to different objectives of optimization, generating information regarding to transportation time, capacity needs, and number of survivors treated in different sizes of the disasters. The DEA allows the estimation of an efficiency rank for each network based on the predefined networks' features. Finally, the regression analysis help to provide a prediction of the index of efficiency calculated by DEA. The index of efficiency (performance measurement) is useful for the emergency managers to:

i. Compare hospital networks alternatives in order to select the network that best cover a defined population, given a set of hospital networks.
ii. Evaluate the impact of adding a new hospital to the network.
iii. Define cooperation policies within an established number of hospitals to participate in the drills required by JCAHO.

In this study, a county is selected for developing this research; however, the methodology can be applied to hospital networks in other counties and cities. The hypothesis to validate this research is the following:

Hypothesis: Network optimization, DEA, and regressions analysis can be combined to create an index of efficiency to measure the performance of the hospital network during a mass casualty disaster.

1.6 Significance of the Study

The significance of this study presents five main aspects, which are enumerated as follows:

i. Expands the understanding of hospital networks capacities in a disaster where there are not sufficient information on the measurement of performance in these disaster situations,
ii. Offers a better health service during a disaster, which is a current concern due to the rise of natural disasters and outbreaks,
iii. Assess hospital coalition's efficiency, which are an increasing practice in the country,
iv. Studies the efficiency in hospital networks for mass casualty and offers general parameters to estimate healthcare coalitions between public and private providers,
v. Generates an index to determine hospital networks' efficiency, based on different approaches that never have been combined before (Network models, Data Envelopment Analysis (DEA), Regression models).

1.7 Contribution

This research develops an efficiency index for hospital networks, which can be used for measuring and monitoring tools to manage a hospital emergency network based on two systems: transportation and hospitals capacity networks. This efficiency index for hospital networks seek to satisfy, in part, the need for performance measures for cooperative planning among hospitals as well as the need of guidelines for determining what constitutes an efficient public health emergency planning network in mass casualty disasters (Hsu *et al*., 2004; Toner *et al,* 2009; Harris and Clements, 2007; Altay and Green III, 2006).

This research presents a combination of three approaches from different areas of knowledge - network optimization, DEA, and regression models - in an effort to expand the understanding of hospital network capacity in a disaster. This understanding and combination of techniques allows the creation of an index of efficiency for hospital networks during mass casualty.

The proposed methodology will support the operational objectives of the 2012 ESF#8 for Florida State to handle risk and response capabilities conducting and participating in training and exercises to test and improve plans and procedures in the hospital response, defining the hospitals that have to participate in each drill or exercise.

In brief, the main objectives of this research seek to propose: (i) a methodology to create an efficiency index based on the understanding of the relationship between two systems (transportation and the hospitals capacity networks), (ii) a mathematical relationship among variables that are part of the index estimated, and (iii) a tool to identify the hospitals that participate in exercises and drills. The application of the methodology proposed will allow the identification of the group of hospitals in a defined area, which should sign mutual aid agreements to improve the hospital response in mass casualty disasters. In addition, this methodology will encourage JCAHO officials to request well-defined drills and exercises to face a mass casualty disaster, defining clearly participants and their roles.

1.8 Outline of this dissertation

The structure of the rest of this dissertation consists of seven chapters. In Chapter 2, the current literature on efficiency in hospital networks is briefly reviewed, and we highlight the fact that current techniques do not offer a tool to support the decision making regarding evaluating the efficiency of predefined hospital networks for disasters. In Chapter 3, we describe the methodology that we propose to answer the gap in the literature, which combines optimization, data envelopment analysis, and regression models. In Chapter 4, we display the data collected regarding hospital and potential disaster locations in the Orlando area used for developing the methodology presented in Chapter 3. In Chapter 5, we develop the optimization models to generate pseudo-optimal hospital networks[6] to deal with two types of disaster scenarios: a hub-spoke hospital network responding to a disaster located in a point that represents the average distance between the hub-hospital and the 12 disaster locations, and a hospital network responding to each of the 12 defined disaster locations. In Chapter 6, we estimated the efficiency of each network though a data envelopment analysis. Chapter 7 presents the regression models estimated to predict efficiency, according to some essential variables. In Chapter 8, a summary of this research and guidelines for future work are given.

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[6] Pseudo-Optimal Network is the optimal network for a given disaster size and hub.

CHAPTER TWO: LITERATURE REVIEW

Once defined the research problem in Chapter 1 "how to measure the hospital networks efficiency for mass casualty", this chapter details the "method of search" used in this literature review, showing the major approaches used to measure efficiency in hospital networks. The "method of search" is a systematic revision of the academic articles published in the last decades, regarding to efficiency performance measurement of hospitals and networks. This literature review distinguishes two focuses of analysis: efficiency analysis and network analysis in hospitals.

2.1 Method

The systematic review includes academic and conference proceedings published between 2000 and 2011 with focus on hospital networks and performance measurement for efficiency. The search strategy used in this systematic analysis used an advanced search in six databases available at UCF Libraries (EBSCO Host, INFORS, IEEEXplore, ISI Web of Knowledge, Wilson Web, ProQuest, and Engineering Village). Using these databases, we searched on the articles' abstracts for the concurrency of the following key words: efficiency, hospital, and network. The search also excluded words, such as computer, electrical, wireless, web, and insurance, in each article. However, since each database has its own subcategories and advance search tools, Table 2 lists all of the details of databases' subcategories selected in this research.

Table 2: Detailed Advanced Search by Database

Database	**Key words**	**Number papers**	**Selected papers**
EBSCO Host	Efficiency, hospital, Network (Abstract) **OR** Efficiency, hospital, Coalitions (Abstract) **Not**: computer, electrical, wireless, web, insurance (TX all Text)	49	4
INFORS	Efficiency, hospital, Network **OR** Efficiency, hospital, Coalitions **Not**: computer, electrical, wireless, web, insurance (TX all Text)	0	0
INFORS	Efficiency hospital Set (Abstract) **Not:** computer, electrical, wireless, web, insurance	21	12
IEEEXplore	Efficiency, hospital, Network (Abstract) **OR** Efficiency, hospital, Coalitions (Abstract) **Not**: computer, electrical, wireless, web, insurance (TX all Text) **Subject:** Communication, networking and broadcasting, general topics for engineers and engineering profession **Types**: Journals, conferences, early access	34	7
ISI Web of Knowledge	Efficiency, hospital, Network (Topic) **OR** Efficiency, hospital, Coalitions (Topic) **Not**: computer, electrical, wireless, web, insurance (Topic) Science Citation Index expanded (SCI-Expanded)	78	10
Wilson Web	Efficiency, hospital, Network (Keywords) **OR** Efficiency, hospital, Coalitions (keywords) **Not**: computer, electrical, wireless, web, insurance (text)	6	0
ProQuest	Efficiency, hospital, Network (Abstract) **OR** Efficiency, hospital, Coalitions (Abstract) **Not**: computer, electrical, wireless, web, insurance (Abstract) Types: Scholarly journal and Dissertations	51	18
Engineering Village (Compendex and Inspec)	Efficiency, hospital, Network (Abstract) **OR** Efficiency, hospital, Coalitions (Abstract) **Not**: computer, electrical, wireless, web, insurance (Abstract) **Subject:** Communication, networking and broadcasting, general topics for engineers and engineering profession Elimination of duplicates 138 to 108	108	18
Total		347	69

The original search generated 347 articles. The selection process of the articles followed two steps. In the first part, the creation of a list of titles for each database and analysis of the selected papers' titles allow the researcher to determine the papers close to hospital networks, efficiency, and performance measurement topics. In the cases, where the paper titles were ambiguous, we read and analyzed their abstracts in order to determinate their inclusion in this research. As a result of this primary selection process, we selected a collection of 69 articles for further reading. Within this research, we found eleven duplicated articles. Thus, we obtained 58 academic articles that accomplished our initial requirements.

In the second step of our selection process, we read each of the 58 abstracts, and then, selected 33 articles as the final research material to analyze thoroughly. After reading all of the papers, we only included 24 out of 33 academic papers in our final research analysis because the focus of the nine articles did not match our research topic. Figure 1 shows the frequency of the distribution of articles published per year between 2000 and June 2011.

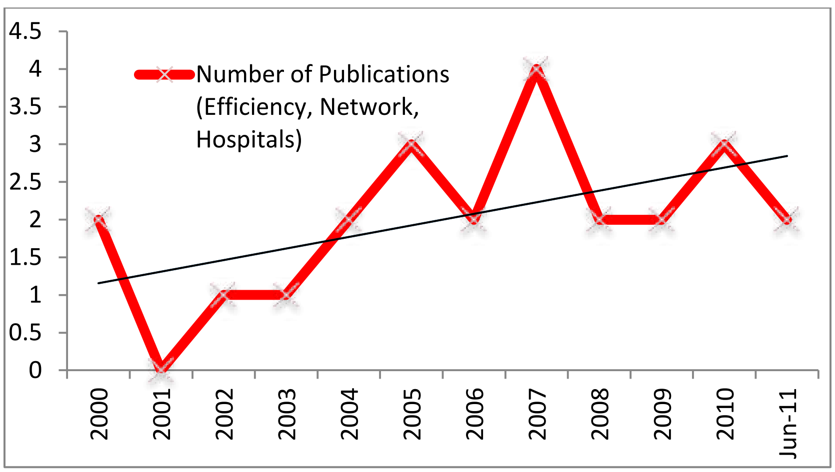

Figure 1: Number of Articles Published

2.2 Findings

This literature review aims to point out the areas that currently have gaps in the study and understanding of emergency care networks. For example, the definition and measure of the successful health care networks are two of the major topics in the emergency management that require more studies (Glickman *et al*., 2010). When we analyzed the 24 articles mentioned at the beginning of this chapter, it was possible to differentiate all according to two focus areas: one oriented to hospital's efficiency analysis, and another oriented towards hospital network analysis.

2.2.1 Hospital's Efficiency Analysis

Scholars have studied hospital's efficiency (Sarkis and Talluri, 2002; Ouellette and Vierstraete, 2004; Chen, Hwang, and Shao, 2005; Aksezer and Benneyan, 2010), using two types of analysis: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis.

2.2.1.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis is one of the most common methods used in evaluating the efficiency among a group of hospitals. The basic linear model developed by Charnes, Cooper and Rhodes in 1978 is based on Farrell's work in 1957 (Sarkis and Talluri, 2002; Ouellette and Vierstraete, 2004).

DEA computes the efficiency frontier, based on the performance of a group of units, which have the same inputs, outputs, and regulations, called as Decision Making Units (DMUs). It is possible to group the models that calculate the efficiency among the DMUs into two: DEA under Constant Returns to Scale (CRS), and DEA under Variable Returns to Scale (VCR). Emrouznejad (2005) implemented DEA using SAS coding. In their study, Aksezer and Benneyan (2010) compared three methods: the Multiple Imputation (MI)[7], the Bootstrapping[8], and the M-0 Method[9] for variable replacement in DEA to minimize the impact of the missing values on the efficiency scores and ranking of the DMUs. The authors consider three levels of missing data 1%, 5%, and 10%, concluding that the MI method estimates the true scores and ranks of the DMUs better than other methods in 10 out of 18 cases. In the following paragraphs, we will summarize the major academic contributions in DEA.

Kuntz and Scholtes (2000) apply DEA to evaluate the hospital capacity-planning problem in Germany. The authors attempt to reduce the number of hospital bed capacity to improve the efficiency of the hospitals. Sarkis and Talluri (2002) proposed an improvement of the DEA, originally proposed by Al-Shammari's in 1999, where they created a ranking system of hospital performance and global benchmarks in DEA. Applying a ranking called the CCR scores, the authors rank hospitals in a three-year period. Since the Sarkis and Talluri's model removes the test unit from the constraint set, an efficiency score (which provides a method for ranking efficient and inefficient units) could be greater than one, allowing the differentiation among efficient units. In addition, Ouellette and Vierstraete (2004) propose a distance function with

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[7] Multiple imputations is a Monte Carlo Simulation technique in which the missing values are replaced by multiple numbers of simulated versions which are estimated from the distribution of the existing data. This method has two assumptions (Aksezer & Benneyan, 2010):

1st Assumption the data at hand must be missing at random

2nd Assumption a probability model for the complete data has to be assumed.

[8] Bootstrapping is a nonparametric technique for making inferences about certain statistical parameters of a population. Bootstrapping treat the sample as if it is the population (Aksezer & Benneyan, 2010).

[9] M-0 Method uses zeros for substitution of the missing output values and employs the same effect on DEA score as removal of that specific output in the calculation of the efficiency of the DMU containing the missing value (Aksezer & Benneyan, 2010).

quasi-fixed inputs[10] to measure the distance between the vector of the input variables and the frontier of production. The authors compare four models, using three different indexes: M (productivity index), E (change in efficiency index), and P (technical change index[11]), concluding that: "Quasi-fixed inputs are a key factor in measuring and explaining productivity and technological change."

According to Chen, Hwang, and Shao (2005), the overall efficiency of a DMU cannot be explained by the same variables that describe the individual efficiency. As a result, the authors compare the results from DEA and the results of the Tobit model[12] to determine the explanatory power of the variables. The Tobit model includes variables that correspond to the following categories: organization structure, management, demographics, and market competition.

Clement, Valdmanis, Bazzoli *et al* (2007) compute a DEA to analyze the hospital efficiency based on quality output, developing two models: (1) the strong disposability of outputs assumption (SDO), and (2) the weak disposability of outputs assumption (WDO). The authors calculate the ratio between SDO and WDO efficiency scores (called congestion) to estimate how much influence the bad outcomes has over the total productivity. Table 3 summarizes the inputs and outputs variables included in DEA.

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[10] Quasi-fixed inputs are inputs that cannot be adjusted to their optimal value even in the long-run (Ouellette & Vierstraete, 2004).
[11] Malmquist index measures the technological change (Ouellette & Vierstraete, 2004)
[12] Tobit model is an econometric model in which the dependent variable is censored developed in 1958 by Tobin. See more details on McDonald, J. F., & Moffitt, R. A. (1980). The uses of Tobit Analysis. *The Review of Economics and Statistics,* 62(2), 318-321.

Table 3: Input Variables and Output Variables Included in DEA

Authors	Input Variables	Output Variables	Type of Analysis
Al-Shammari (1999)	Bed Days Physicians (full-time) Health Personnel (full-time)	Patient days Minor surgical operations Major surgical operations	DEA
Kuntz and Scholtes. (2000).	N^o beds Annual cost of care	Cases per year	DEA
Sarkis and Talluri (2002)	Bed days Physicians Health personnel.	Patient days, Minor operations Major operations.	DEA
Ouellette and Vierstraete (2004)	*Variables inputs* Hours worked excluding physicians Expenditure on furniture and equipment *Quasi-fixed inputs* N^o of stretchers FTE physicians	N^o cases	DEA with quasi-fixed inputs
Chen, Hwang, and Shao (2005).	General Service costs Routine and special care costs Ancillary service costs Cumulative capital investment cost ***Tobit Regression***: Organization structure, Management, Demographics, and Market competition.	Routine care bed-days, Special care bed-days	DEA and Tobit Regression
Emrouznejad (2005)	Staff hours per day Suppliers per day	Total Medicare plus Medicaid-reimbursed patient days Total privately paid patient days	DEA and Malmquist Index
Clement *et al*. (2007)	*Labor inputs* FTE registered nurses FTE licensed practical nurses FTE other *Capital Inputs* Staffed beds	Births Outpatient surgeries Emergency room visits Outpatient visits Case mix adjusted admissions	DEA Congestion index (SDO/WDO)
Aksezer and Benneyan (2010)	N^o patient beds N^o doctors N^o supporting medical staff N^o specialist appointments taken	N^o outpatients visits N^o emergency visits N^o surgeries performed	DEA

2.2.1.2 Stochastic Frontier Analysis

The stochastic frontier analysis (SFA) is a common approach in the empirical analysis of efficiency and productivity. Aigner, Lovell, and Schimdt (1977) and Meesun and van den Broeck (1977) developed the basic models of SFA (Koop and Steel, 2001), where SFA capture the maximum number of outputs from a given level of inputs. The deviation of the frontier is a measure of inefficiency.

Rosko and Proenca (2005) assess the impact of network and system use to provide services on hospitals, using X-inefficiency[13] and Stochastic Frontier Analysis (SFA). Gao, Campbell, and Lovell (2006) propose a framework that can be used to guide an equitable resource allocation, and identify inefficiency, based on SFA. In addition to the traditional inefficiency concepts, the authors suggest to include the overutilization of resources and over-consumption. They also believe that "patients shared" among different healthcare services is a significant factor to measure efficiency. Gao, Campbell, and Lovell (2006) conclude that when diverse medical centers host more "patients shared," the services and procedures delivered for any single medical institution decrease drastically. According to the same authors, there are not high correlation between teaching hospitals and higher costs.

Kumar and Nunne (2008) compare the efficiency of general hospitals with specialized hospitals in the Unites States using SFA. The researchers simulate the data using realistic assumptions from available information. The authors use a modified version of the Cobb-Douglas cost function, including severity of patients to measure technical efficiency. The Kumar and Nunne's results suggest that specialized hospitals are likely more efficient than general hospitals.

Granderson (2011) evaluate the relationships between hospital cost efficiency and the hospital alliance membership. He concludes that membership in larger groups contributed to the

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[13] According to Rosko and Proenca (2005) X-inefficiency is the difference between optimal performance and actual performance. X-inefficiency may be due to any of the following types of inefficiency: technical, allocative, scale, or scope. For more details see Frantz, R. S. (1997). *X-Efficiency: Theory, Evidence and Applications* (1st ed.). Springer.

improvement of cost efficiency. However, membership in an additional network did not help to enhance hospital cost efficiency (Granderson, 2011). Table 4 depicts variables and the cost models included in SFA models.

Table 4: Variables and the Cost Models Included in SFA

Authors	**Variables recommended**	**Cost model**	**Type of Analysis**
Rosko and Proenca (2005)	Total Expenses Adjusted discharges Outpatient visits Other days : Days in long-term units Emergency visit Outpatient surgery COTH member: (1,0) for hospitals that are members of the council of teaching hospitals Other teaching hospital: (1,0) for teaching hospitals that are not COTH members Price of capital: Depreciation and interest expenses per bed Price of labor: Annual salary per full-time equivalent employee	Translog cost function	**SFA** X-inefficiency
Gao, Campbell, and Lovell (2006)	Overutilization of resources Over-consumption Patient shared among healthcare services	Cobb-Douglas cost function	**SFA**
Kumar and Nunne (2008)	Cost per discharge per state Comp cost discharge per state Cap cost discharge per state Supply cost discharge per state Insurance Cost per discharge per state Severity of the patients	Cobb-Douglas cost function	**SFA**
Granderson (2011)	***Input*** Labor measure: N^{o} FTE hospital personnel Capital measure: Hospital beds regularly set up and staffed for inpatient use. Labor price: the sum of payroll expenses and employee benefits is divided by the quantity of labor. Capital price: the sum of hospitals expenditures on building, fixtures, and moveable equipment are divided by the quantity of capital. ***Output*** N^{o} hospital outpatient and inpatient surgeries Outpatient visits Inpatient days Case mix-adjusted discharges	Farrell measure of cost efficiency	**SFA**

2.2.2 Hospital Network Analysis

Various techniques analyze hospital networks. For example, Williams and Lake (2000) use artificial neural network to analyze health information. They use the data mining[14] technique to make subgroups from two data sets created by the UK National Health Service indicators. These authors classify hospitals in subgroups using indicators reflecting departmental structure, efficiency and quality measures. The main indicators of efficiency considered by Williams and Lake (2000) are average length of consultant episodes, average number of days from start of the episode to operation, and percentage of elective admissions that waited over 12 months.

Su and Shih (2003) simulate 23 networked-emergency medical services (EMS) hospitals affiliated to 36 emergency response units. This analysis compares four alternatives to coordinate hospital network and emergency services, providing a two-tier rescue service. The first alternative assigns one fixed hospital network to each emergency response, while the second assigns a variable number of two tier rescue units to each hospital network based on the utilization rate and the probability of waiting time of patients for rescue. In the third option, each emergency service subgroup can cooperate with two or three hospital networks, following a distance criterion. Finally, the fourth alternative, the dispatch rate of the two–tier rescue is variable. Su and Shih (2003) conclude that a dispatch model with two hospitals in prearranged sequence is better than other alternatives to reduce the waiting time for rescue.

Daucourt, *et al*. (2006) improve the performance of a teleradiology network using a telemedicine system, which allows to manage remote emergencies and elective radiology consultations. The measures used to evaluate the performance are the following: the proportion

[14] Williams and Lake (2000) used a Kohonen Self-Organizing Map technique to group two data sets.

of transfers, hospitalizations, and consultations avoided. Aktaş, Ülengin, and Önsel, (2007) proposed the total time spent in the system or length of stay, as other measure of performance to measure efficiency in healthcare.

Ferrier and Valdmanis (2004) compare merged hospitals' productivity, using the hospital indicators (before and after hospital merged), and a hospital group control. These authors use Farrell efficiency[15], pure technical efficiency[16], scale efficiency[17], and Malmquist index[18] to measure the efficiency of the merged hospital productivity.

To represent waiting times in accident and emergency departments, Marshall and Bums (2007) use a Bayesian network hybrid model. The Bayesian network generates an outcome used by the survival distributions. The last node of the Bayesian network is a variable, which indicates if a patient should be admitted in a hospital. This last node influences on patients trolley wait. The authors claim that "the model is a means of demonstrating the methodology where patient information, known on arrival to an A&E department, which helps to predict the future outcome of the patients and their associated trolley wait."

In order to reduce the time to response to an emergency from 12 minutes to 6.94 minutes, Gee (2007) establishes a community EMS first-responder program. The author settles first responders in all areas within the county and estimate the number of responders distributed in the

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[15] According to Ferrier and Valdmanis (2004), Farrell efficiency is a measure of technical efficiency input-oriented. For more details see Farrell MJ (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, Series A (General) *120*: 253-281

[16] According to Ferrier and Valdmanis (2004), Pure technical efficiency capture the overuse of input given the observed scale of output. For more details see Ganley JA and Cubbin JS (1992). Public Sector Efficiency Measurement-Applications of Data Envelopment Analysis. North-Holland: Amsterdam.

[17] According to Ferrier and Valdmanis (2004), Scale efficiency measures the overuse of inputs caused by operating at non-constant returns to scale. For more details see Ganley JA and Cubbin JS (1992). Public Sector Efficiency Measurement-Applications of Data Envelopment Analysis. North-Holland: Amsterdam.

[18] Ferrier and Valdmanis (2004) used the input-oriented Malmquist index of productivity change. For more details see Sudit, E. F. (1996). *Effectiveness, Quality and Efficiency: A Management Oriented Approach* (1st ed.). Springer.

same county, following geographical population distribution and population concentration. Gee (2007) proposes to implement courses and a well-equipped jump bag (oxygen canisters, and automatic defibrillators) to each first responder within a community EMS first-responder program.

The referral patterns for patients into a cardiological network are the main interest for the research developed by Bruni, Nobilio, and Ugolini (2008). The authors analyze the referral patterns for patient into a cardiological network in order to develop a close referral link between the highly specialized centers (hubs) and the network of satellite units (spokes). The position of the hubs and spokes reflects the geographical and demographic needs of the region. Their study proposes two-step analysis: in the first step, they calculate the entropy indexes, and in the second step, they use the gravity model and Bayesian techniques for modeling the patient flows in the system. The authors discovered in their study that three of the nine Italian provinces seem to deviate from the purpose of provincial self-sufficiency.

Iwashyna, Christie, Moody, *et al* (2009) describe the existing acute care network in terms of the pattern of transfers. Hospitals are the nodes in the network and the transfers of critically ill patients are the pathways between nodes. These pathways can be two-way or one-way. The pathways present different sizes according to the total number of patients moving one way or another between hospitals. Iwashyna *et al*. (2009) compute a centrality index for each hospital. This index represents the number of patients received from different hospitals.

Janosikova (2009) proposes criteria such as quality, complexity, accessibility, and equity to reduce a hospital network. The author defines each criterion to quantify benefits of the reduction of the network. The quality criterion identifies two categories to classify the hospitals: general hospital and teaching hospital. The complexity criterion is a ratio between the number of emergency departments and a minimum number of departments defined by the author. This minimum number is six, which include the following departments: surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics.

Sultanow and Weber (2010) developed a visualization model for collaborations in distributed organizations and disaster scenarios, using semantic network, GIS, and Web3D to visualize and navigate information in multi-tiers. The authors depict the essential characteristics of a coalition in a model of three levels: world or macro view, location or meso view, and organization unit or micro view.

Finally, in order to define boundaries for networks in healthcare, Glickman *et al*. (2010) claim that geographical aspects, market–based, or government assignments can support the creation of boundaries for healthcare networks. Table 5 presents a summary of the main findings in hospital networks analysis.

Table 5: Variables Included in Hospital Network Analysis

Authors	Variables to measure efficiency	Approach
Williams and Lake (2000)	Average length of consultant episodes Average number of days from start of episode to operation Percentage of elective admission that waited over 12 months.	Data Mining
Su and Shih (2003)	Call waiting time (min) Advanced life support (ALS) event-site arrival time (min) Patient hospital arrival time (min) Utilization rate of ALS rescue (%)	Simulation
Daucourt, Sicotte, Pelletier-Fleury, Petitjean, Chateil, and Michel (2006)	Proportion of transfers avoided Hospitalizations avoided Consultations avoided	Telemedicine system
Aktaş, Ülengin, and Önsel (2007)	Time spent in the system or length of stay	Bayesian Belief Network
Ferrier and Valdmanis (2004)	***Input Variables*** Staffed beds Full time equivalency (FTE)physicians FTE medical residents FTE registered nurses FTE other personnel ***Output Variables*** Adjusted admissions Total number of surgeries Number of emergency room visits	Farrell efficiency Pure technical efficiency, scale efficiency and Malmquist index.
Marshall and Bums (2007)	Survival distributions	Bayesian network hybrid model
Gee (2007)	Time to response Geographical population distribution Population Concentration	Management (trainee and equipment for first responders)
Bruni, Nobilio, and Ugolini (2008)	Pattern transfers	Hub and spoke model Entropy indexes Gravity model Bayesian techniques
Iwashyna, Christie, Moody, Kahn, and Asch (2009)	Pattern transfers	Centrality index
Janosikova (2009)	***Criteria to reduce a hospital network*** Quality, Complexity, Accessibility, Equity	Optimization Multi-objective
Sultanow and Weber (2010)	Information for Collaboration in Distributed Organizations and Disaster Scenarios	Semantic network, GIS and Web3D to visualize and navigate information in multi-tiers
Glickman, Delgado, Hirshon, Hollander, Iwashyna, Jacobs, Kilaru, *et al.* (2010)	***Boundaries of the networks in health care*** Geographical boundaries, Market –based, By the government	Panel Analysis

2.3 Discussion of the Research Gaps

The network hospital efficiency depicts different gaps in the literature, according to the survey conducted in this work. Most of the models for efficiency analysis are not under disaster conditions, probably due to lack of data that can mimic disaster scenarios (e.g. information of victims' transfer time, patient patterns among hospitals). Table 6 depicts that most of the research in efficiency are for single hospitals, presenting a low rate of coalitions or hospital networks studies.

Finally, the majority of the studies involve a significant amount of data, as Table 6 and Table 7 show. This literature review helps to distinguish two major gaps in the research area of efficiency performance measurement for hospitals networks, which are the following:

1. The lack of a set of variables that can compare the efficiency of the hospital networks for a mass casualty disaster.
2. The lack of a methodology that can evaluate the efficiency of the hospital networks for a mass casualty disaster.

This research aims to address these two gaps in the literature, creating an index to compare different hospital response networks based on efficiency principles. This index does not require a large amount of data to calculate the efficiency of hospital network. Furthermore, this allows the emergency managers to compare different predefined hospital networks to improve the response during and after a mass casualty disaster.

Table 6: Summary of Approaches for Efficiency Hospital Network

Efficiency Hospital Network	**Applications**	**Advantages**	**Disadvantages**	**Authors**
DEA	Efficiency measurement Hospital Capacity planning Ranking hospital performance Establishing global benchmarks	No parametric, Network applications.	Not including stochastic behavior, No studies for mass casualty, Need a large amount of data, Need consistency by period.	Al-Shammari (1999) Kuntz and Scholtes. (2000) Sarkis and Talluri (2002) Ouellette and Vierstraete (2004) Chen, Hwang, and Shao (2005). Emrouznejad (2005) Clement *et al.*(2007) Aksezer and Benneyan (2010)
SFA	Efficiency Comparison between general and specialty hospitals. Evaluate the impact of the network on the providing service at hospitals Evaluate impact of the membership to alliance on the hospital cost efficiency	Network applications, Including stochastic behavior.	No studies for mass casualty, Definition of Cost model, Need prices and values, Need a large amount of data, Need consistency by period.	Rosko and Proenca (2005) Gao, Campbell, and Lovell (2006) Kumar and Nunne (2008) Granderson (2011)
Simulation	Comparison of hospitals network alternatives for emergency	Network applications, Considering emergency conditions.	Need distributions probabilities, Need of patterns of transferences.	Su and Shih (2003)
Optimization Multi-objective	Reduce hospital Networks based on quality, complexity, accessibility, and equity	Capturing multiple features at the same time.	Optimization for one scenario.	Janosikova (2009)
Conceptual models	Model for collaboration in disaster scenarios	General overview.	High level approach.	Sultanow and Weber (2010) Glickman *et al*. (2010)
Data mining	Classification of hospitals according quality, efficiency and departmental composition	Find relationships among different variables.	Individual hospitals No studies for mass casualty.	Williams and Lake (2000)
Efficiency index	Comparison of hospitals before and after merger	Ranking of hospitals.	Compare individual hospitals.	Ferrier and Valdmanis (2004)
Gravity models	Localization of resources Analysis of patients transferences patterns	Simple.	Need of other models.	Gee (2007) Bruni *et al*. (2008) Iwashyna *et al*.(2009)
Entropy model	Analysis of patients transference patterns	Simple.	Need of other models.	Bruni *et al*. (2008)

Table 7: Summary of Variables Relevant in Efficiency Hospital Network Analysis

Hospital Resources Variables	**Approach**
Bed Days	DEA, SFA, Efficiency Index (single hospital)
FTE Physicians	DEA, SFA, Efficiency index (single hospital)
FTE Health Personnel	DEA, SFA, Efficiency Index (single hospital)
N^{o} Specialist appointments taken	DEA
Hospital Performance Variables	**Approach**
Patient Days	DEA, Data mining
Minor surgical operations	DEA, SFA
Major surgical operations	DEA
Medicaid-reimbursed patient days	DEA
Case mix adjusted admissions	DEA, Efficiency Index (single hospital)
Case mix-adjusted discharges	SFA
Severity of Patients	SFA
N^{o} outpatients visits	DEA, SFA
N^{o} emergency visits	DEA, SFA
Patient Shared	SFA
Overutilization of resources	SFA
Over-consumption	SFA
Proportion of transfer avoid	Telemedicine
Response Performance Variables	**Approach**
Advanced life support (ALS) event-site arrival time (min)	Simulation
Time to response	Simulation, Management
Time spent in the system or length of stay (LOS)	Bayesian Belief Network
Utilization rate of the advanced life support	Simulation

CHAPTER THREE: METHODOLOGY

The literature review elaborated in Chapter 2 lists the most recent academic works regarding network efficiency for mass causalities. Those works were useful to see how scholars have recently been defining and analyzing the different theoretical aspects and applications related to efficiency in hospital networks. Chapter 2 shows that the most common approaches to estimate efficiency are DEA and SFA, while to study network analysis is operations research. However, there is not abundant scholar works that measure the hospitals network efficiency for mass causalities. For that reason, this research develops a methodology, which creates an index to compare different predefined hospital response networks based on efficiency principles, combining network optimization, data envelopment analysis (DEA), and regression models. This Chapter describes the main techniques found in the literature review that are incorporated into the methodology proposed in this chapter. Moreover, in this methodology, the optimization models are used to select hospitals that should be included in a response network in case of a disaster occurrence. In order to estimate the efficiency of these hospital networks, we propose to apply DEA and run regression models to find mathematical relationships between efficiency and characteristics of the network.

3.1 Network Optimization

Network design optimization is an integration of graph theory and optimization methods. A network is a connected graph "G" with finite number of nodes "N", and a set of pairs of nodes called arcs "A" (Gen, Cheng and Lin, 2008)[19]. These arcs can be oriented with restrictions on their flow among nodes based on their arcs capacity and direction (Taha, 2007, p.236).

In this research, we apply the transshipment or a minimum-cost flow problem model, which includes a single commodity and a linear cost function (Nohria and Eccles, 1992). Table 8 displays Janosikova's formulation for a discrete network location problem for hospitals (Janosikova, 2009). The Janosikova's model seeks to reduce the public hospital network in the Slovak Republic to decrease public costs. The author proposes the allocation of patients to the open hospitals based on the following criteria: quality of the hospitals, complexity of the hospitals, transportation accessibility, and equitable distribution of the hospitals among citizens. Even though, Janosikova's work does not seek the same objective of this research, we took his definition of complexity, "the ability of the hospitals to provide urgent health care," to define the variable hospital services for each network. As a result, we consider the same services (surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics) defined by Janosikova to determine the services in our network optimization.

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[19] Gen, M., Cheng, R., & Lin, L. (2008). Network Models and Optimization: Multiobjective Genetic Algorithm Approach. Springer.

Table 8: Janosikova's Mathematical Formulation of a Hospital Network

Criteria	**Formulation**
Quality q_i = quality y_i {0,1}; y_i = 1, if the hospital i is included in the network; y_i = 0, otherwise	$Max\ f_1(y) = \sum_{i \in l} q_i y_i$
Urgent care O_i = Emergency department ratio	$Max\ f_2(y) = \sum_{i \in I} O_i y_i$
Accessibility t_{ij} =Time requested to get from municipality j to hospital i (this time is function of the speed) b_j = inhabitant in municipality j x_i {0,1}; x_i = 1, if the hospital i is the nearest one to municipality j; x_i = 0, otherwise	$Min\ f_3(x) = \sum_{i \in I} \quad \sum_{j \in J} t_{ij}(v) b_j\, x_{ij}$
Equitable t_{ij} =Time requested to get from municipality j to hospital i (this time is function of the maximum time to cover a municipality)	$Min\ f_4(x) = \sum_{i \in I} \quad \sum_{j \in J} t_{ij}(u) b_j\, x_{ij}$ $t_{ij}(u) > T^{max}$

The multicriteria optimization by a scalarization method

Maximize $\quad w_1 f_1(y)/N_1 + w_2 f_2(y)/N_2 - w_3 f_3(x)/N_3 - w_4 f_4(x)/N_4$

Subject to

$$\sum x_{ij} = 1\ for\ j \in J \qquad (each\ municipality\ is\ assigned\ to\ one\ hospital)$$

$$x_{ij} \le y_i\ \ for\ i\ \in I, j \in J \qquad (a\ municipality\ j\ is\ assigned\ to\ an\ open\ hospital\ i)$$

$$\sum_{i \in I} y_i = p \qquad (the\ number\ of\ open\ hospital\ is\ limited\ by\ p)$$

$$N_1 = \sum_{i \in I} q_i \qquad (a\ normalizing\ factor)$$

$$N_2 = \sum_{i \in I} O_i \qquad (a\ normalizing\ factor)$$

$$N_3 = \sum_{j \in J} b_j t_{i(v,j),j}\ (v) \quad (\ a\ normalizing\ factor)$$

$$N_4 = \sum_{t_{i(u,j),j}(u) > T^{max}} b_j t_{i(u,j),j}\ (v) \quad (\ a\ normalizing\ factor)$$

$$y_i\ \in \{0,1\} for\ i\ \in I\ (binary\ variable)$$

$$x_{ij}\ \in \{0,1\} \quad for\ i\ \in I, j \in J\ \ (binary\ variable)$$

$w_k \ge 0$ for all k=1, 2,3,4 (weight which expresses the importance of the kth objective)

$$\sum_{k=1}^{4} w_i = 1 \quad (the\ sum\ of\ weights\ for\ each\ objective)$$

3.2 Data Envelopment Analysis

The output to input ratio is the basic measure of performance in most organizations. This ratio defines partial productivity and needs to indicate the units of ratio, such as units to time, and units to worker hours. Furthermore, this ratio does not allow multiple inputs and outputs evaluation though the combination of different types of inputs and outputs, which may have different measurement units. Another disadvantage, even if it is possible to combine multiple inputs and outputs with the same units, it is not possible to know the relative weight of each input and output in the final product or activity. Data Envelopment Analysis (DEA) is a method that allows researchers to calculate efficiency without such problems.

DEA is one of the most popular non-parametric methods to evaluate comparative or relative efficiency (Thanassoulis, 2001). Charnes, Cooper, and Rhodes propose the basic DEA model also known as CCR Model in 1978, based on Farrell's seminal work title:"The Measurement of Productive Efficiency" published in 1957 (Cooper, Seiford and Zhu, 2011).[20]

Prior to applying DEA, it is necessary to establish appropriate units of assessment, called the Decision Making Units (DMUs). The DMUs “should be homogeneous entities in the sense that they use the same resources and produce the same outputs” (Thanassoulis, 2001, p.21). Thus, each j DMU (j=1,2,...,n) uses a set of m inputs x_{ij} (i=1,2,...,m) to produce s outputs y_{rj} (r=1,2,...,s).[21] Then, DEA calculates the efficiency frontier based on the performance of this

[20] Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Data Envelopment Analysis: History, Models, and Interpretations. In W. W. Cooper, L. M. Seiford, J. Zhu, F. S. Hillier, & C. C. Price (Eds.), Handbook on Data Envelopment Analysis, International Series in Operations Research & Management Science (Vol. 164, pp. 1–39). Springer US. Retrieved from http://www.springerlink.com/content/j204w55hjrh30231/

[21] Some additional conditions guide the selection of inputs and outputs to analyze DMUs, such as: (i) numerical data should be available for each input and output and they are positive values for the basic model; (ii) the selected

group of *n* DMUs. As a result, some of the DMUs will be on the efficiency frontier and some of them will be under. The efficient frontier includes the set of all CCR- Efficient DMUs.

According to Cooper, Seiford and Tone (2000, p. 23), the linear program (LPo, primal model or multiplier model) associated to CCR model is the following:

LP_o $\quad\quad$ $\text{Max } \theta = \mu_1 y_{10} + \ldots\ldots\ldots + \mu_s y_{s0}$ (3.1)

Subject to:

$\nu_1 x_{10} + \ldots\ldots\ldots + \nu_m x_{m0} = 1$ (3.2)

$\mu_1 y_{1j} + \ldots\ldots\ldots + \mu_s y_{sj} \leq \nu_1 x_{1j} + \ldots\ldots\ldots + \nu_m x_{mj} \quad (j = 1, \ldots, n)$ (3.3)

$\nu_1, \nu_2, \ldots, \nu_m \geq 0$ (3.4)

$\mu_1, \mu_2 \ldots, \mu_s \geq 0$ (3.5)

Where:

m: number of inputs

s: number of outputs

n: number of DMUs

x_{ij} : input i for DMU j

y_{sj} : output s for DMU j

ν_i : input weights or multiplier (yet unknown) (i=1,…,m)

μ_r : output weights or multiplier (yet unknown) (r=1,…,s)

The dual problem corresponding to the CCR-Model also known as the envelopment model, seeks to determinate the CCR-efficiency value θ^*. The dual problem is formulated as follows:

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inputs, outputs and DMUs should indicate a management interest; (iii) small inputs and large output are preferable; (iv) measurement units of inputs and outputs do not need to be similar (Cooper, Seiford and Tone, 2000).

DLPo min θ (3.6)

Subject to

$\theta x_o - X\boldsymbol{\lambda} \geq 0$ (3.7)

$\mathbf{Y}\boldsymbol{\lambda} \geq y_o$ (3.8)

$\boldsymbol{\lambda} \geq 0$ (3.9)

The CCR- Model is resolved in two phases to obtain the input excesses and output shortfalls. First, the dual problem is resolved, obtaining the CCR-efficiency value (θ^*)[22]. Second, the value of θ^* is incorporated into a new linear problem to find a solution that maximizes the sum of input excesses and output shortfalls. This new linear problem then becomes

LP $max\ \omega = es^- + es^+$ (3.10)

Subject to

$s^- = \theta^* x_0 - X\boldsymbol{\lambda}$ (3.11)

$s^+ = Y\boldsymbol{\lambda} - y_0$ (3.12)

$\boldsymbol{\lambda} \geq 0,\ s^- \geq 0, s^+ \geq 0$ .... (3.13)

Where

e is a vector of ones, $es^- = \sum_{i=1}^{m} s_i^-$ and $es^+ = \sum_{r=1}^{s} s_r^+$

The optimal solution for the second phase is called the max-slack solution. For the cases where $s^{-*} = 0$ and $s^{+*} = 0$, this solution is known as zero-slack (Cooper, Seiford, and Tone, 2000, pp.42- 45)

The optimal solution for LPo computes the weights or multipliers ($\boldsymbol{\nu}^*, \boldsymbol{\mu}^*$) for the DMUo. This set includes the most favorable weights for the DMUo since it maximizes the ratio scale given by:

---

[22] CCR-Efficiency is also called Farrell Efficiency

$$\theta^* = \frac{\sum_{r=1}^{s} u_r^* y_{ro}}{\sum_{i=1}^{m} v_i^* x_{io}} \tag{3.14}$$

From (17), the denominator is 1, so

$$\theta^* = \sum_{r=1}^{s} u_r^* y_{ro} \tag{3.15}$$

Thus, v_i^* is the optimal multiplier for the input *i* and its magnitude indicates the relative importance of the input *i*. Correspondingly, u_r^* indicates the relative importance of the output *r* (Cooper, Seiford and Tone, 2000).

In addition, convexity and in efficiency properties allow to develop a piecewise linear approximation to the efficient frontier and the area dominated by the frontier. The definition of CCR-Efficiency is the following (Cooper, Seiford & Tone, 2000, p. 24):

"1.- DMU is CCR-efficient if $\theta^*= 1$ and there exits at least one optimal (ν^*,μ^*), with $\nu^* > 0$ and $\mu^* > 0$.

2.- Otherwise, DMU_o is CCR-inefficient."

As a result, if $\theta^* <1$ or $\theta^* = 1$, and at least one element of (ν^*,μ^*) is zero, for every optimal solution of LPo, then it claimed a CCR-inefficiency. If a DMU_o is CCR-inefficient, $\theta^*<1$, then at least one DMU_o has the weight (ν^*,μ^*), which produce equality between the left and right side, so θ^* could be enlarged. The DMUs that accomplish this latter condition belongs to the reference set for the CCR-inefficient DMU_o. This reference set is defined based on the maximum slack solution. (Cooper, Seiford & Tone, 2000, pp. 24-25, 47)

In addition, DEA models assume the production possibility set *P* is convex. In other words, if two points (x_1,y_1) and (x_2,y_2) belong to *P*, then any other point in the line connecting these two points belongs to *P*.[23] Additional properties of the production possibility set include the constant returns-to-scale assumption.[24] According to this assumption, there are two models to calculate the efficiency among the DMUs, which are DEA under Constant Returns to Scale (CRS) and DEA under Variable Returns to Scale (VRS).

In addition, CCR models present two versions, one called input-oriented model (CCR-I) and another output-oriented model (CCR-O). The input-oriented model minimizes the input levels keeping the outputs at given levels or larger, on the other hand, the output-oriented model maximizes the output levels keeping the input at given levels or lower.

Finally, DEA has two main advantages (i) identify amount of inefficiency in each input and output for each DMU and (ii) identify the benchmark members for inefficient DMUs (Cooper, Seiford, and Tone, 2000, p.14). To ensure a powerful DEA, the number of DMUS must exceed the number of the combined total of inputs and outputs by at least twice (Drake and Howcroft, 1994, p.83).

3.5 Methodology

This research proposes a methodology that integrates optimization and frontier analysis approaches to obtain an efficiency index to determine before, efficient cooperative-networks

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[23] **Convexity property**: $\sum_{j=1}^{n} \lambda_j x_{ij}$ (i=1,2,...,m) and $\sum_{j=1}^{n} \lambda_j y_{rj}$ (r = 1,2,...,s) are possible inputs and outputs achievable by the DMU_j, where λ_j (j=1, ...,n) are nonnegative scalars such as that $\sum_{j=1}^{n} \lambda_j = 1$ (Zhu, 2009, p. 3)
[24] "If an activity (x,y) belongs to P, then the activity (tx,tv) belongs to P for any positive scalar t" (Cooper, Seiford, and Tone, 2000, p.42)

among hospitals to conduct the response to mass casualty disasters. Then, a regression analysis is used to predict the index of efficiency. The methodology has three stages: Index Data Generation, Index Prediction, and Indexes Comparison. Figure 2 depicts the interrelation among the three stages of analysis.

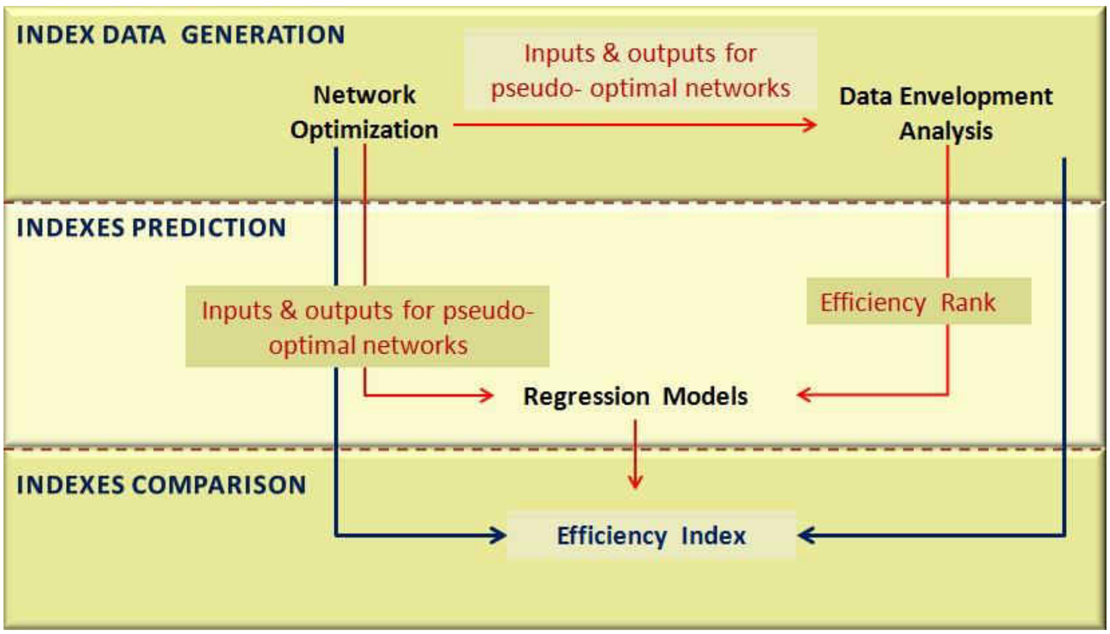

Figure 2: Methodology Diagram

The index data generation phase uses network optimization models and DEA techniques to create data to feed a regression model. In the index prediction stage, the equation resulting in the regression seeks to estimate the efficiency of a hospital network according to the dependent variables predefined in the previous stage. Finally, the efficiency indexes are compared in the third stage.

The assumptions included in the proposed methodology are the following:

- Ambulances transport all of the survivors.
- There are enough ambulances to transport the survivors from the disaster location to hospitals
- The number of visitors in each potential disaster locations is the same any day of the year, so the disaster locations have been selected according to the high number of daily visitors.
- The survivors can wait for more than 1 hour to receive medical care.
- All of the hospitals can work together no matter they belong to different owners.
- The disaster has the same percentage of people younger than 14 years old in Orlando. The percentage of children survivors is 20% of the total number of survivors in each scenario.
- The available bed capacity in the Emergency Departments of hospitals in the Orlando area is 47%.
- All the hospitals in the network provide the same services except by the children hospitals that provide services for children only.
- All types of the disasters produce the same type of injuries.

3.5.1 Data Generation

The network optimization problem and the DEA create information to feed the regression model. The network optimization, the first part of the Index Data Generation phase, generates a set of pseudo-optimal hospital networks[25] using two optimizations and three disaster sizes (See Figure 3). An optimization attempts to minimize the distance between hospitals while another seeks to minimize the distance between hospital and potential disaster locations.

The definition of disaster's sizes depends on the number of survivors at the disaster's location. As a result, three disaster's sizes were defined for this research, small, medium, and large. For each pseudo-optimal network created, we calculate the number of emergency beds, the average distance between hospital and disaster location, the number of hospitals in the network, the average services offered in the network, and the number of survivors allocated in less than a 40 miles range. The information obtained in each network is an input or output of the Data Envelopment Analysis. Figure 3 displays a diagram including optimization objectives, disaster sizes, and input and output expected.

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[25] Pseudo-Optimal Network is the optimal network for a given disaster size and hub.

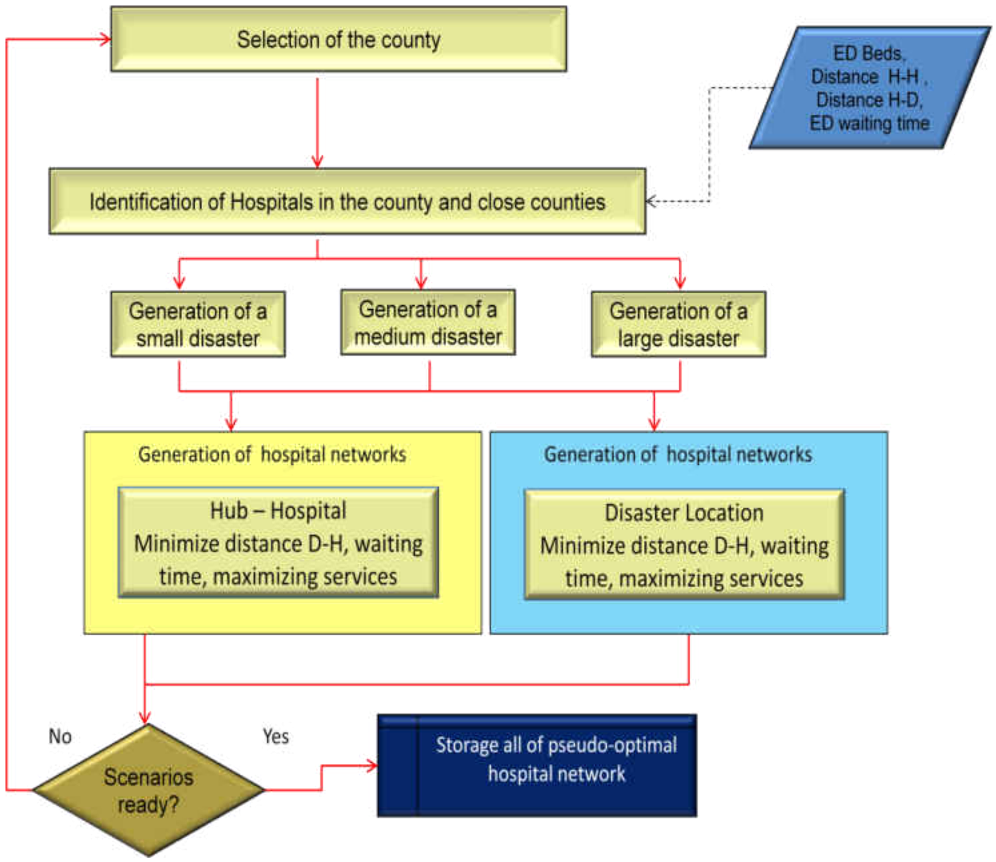

Figure 3: Data Generation Network Optimization Diagram

The second part in the Index Data Generation stage is the application of DEA to calculate the efficiency for each pseudo-optimal network. This DEA considers each pseudo-optimal network as a Decision Making Unit (DMU) to calculate the efficient frontier and the magnitude of the efficiency relative for each of DMU. Then, it is possible to differentiate the hospital network located on the efficient frontier, and those that are not on the efficient frontier. The pseudo-optimal networks located on the efficient frontier are efficient, while the ones that are not located on the efficient frontier are not efficient. Figure 4 displays the relationship between the optimization and the DEA.

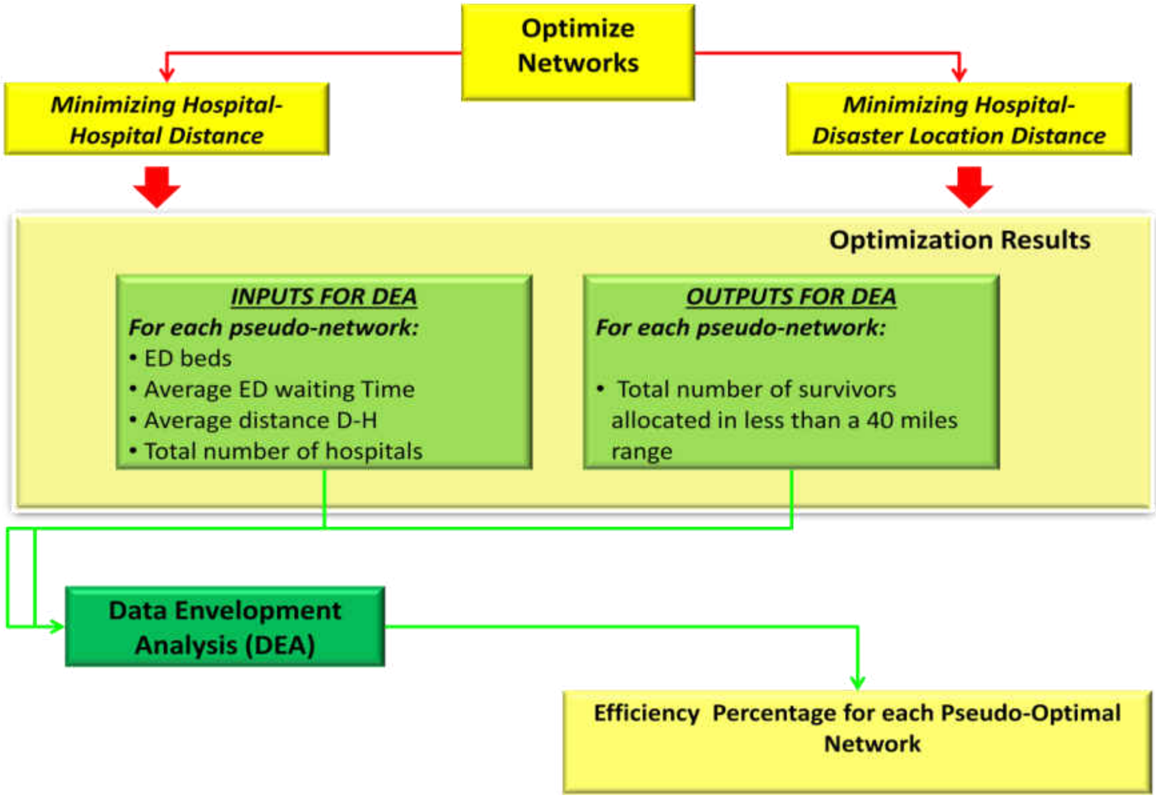

Figure 4: Index Data Generation DEA Diagram

3.5.2 Index Prediction

The Index Calculation stage computes a multiple regression using the information generated by the optimization and the efficiency level calculated by DEA. Figure 5 exhibits the Index Calculation phase, showing the relationship among DEA, network optimization, and the regression model. The result expected from this stage is a mathematical relationship between hospital network characteristics and network efficiency.

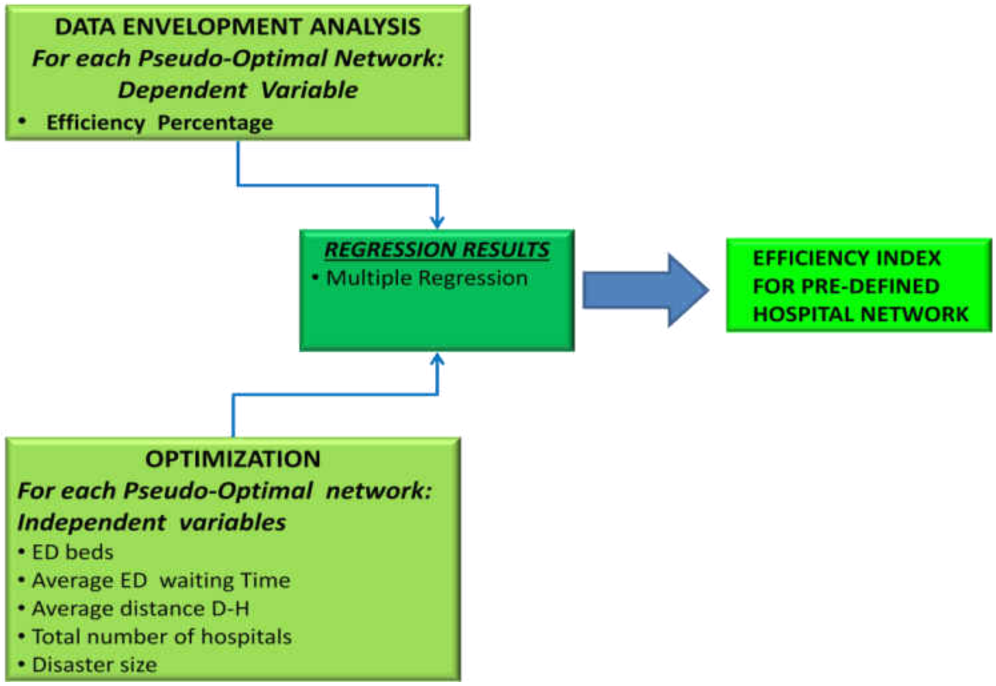

Figure 5: Index Prediction Diagram

3.5.3 Indexes Comparison

This stage determines if the indexes predictors can estimated the efficiency for hospital networks computed by DEA. In this phase, the indexes are compared to select which one is the best regression to predict the efficiency in the networks. It is important to mention that we will not use the complete data set to develop a regression model in order to validate with a different set of networks[26].

[26] We try to validate the index with information provided by Orange County Health Department (OCHD), using a Turing test. However, it was not possible with the information gave by emergency managers of the two main chain of hospitals in the Orlando area.

CHAPTER FOUR: DATA COLLECTION

The data regarding to potential disaster sites and hospitals characteristic are very relevant in order to apply the methodology proposed in Chapter 3. For that reason, Chapter 4 is dedicated to display and explain all the data needed to perform the proposed methodology in the Orlando area. This chapter begins identifying the hospitals located in the Orlando area, estimating their Emergency Department (ED) bed capacities, medical services, and the distances between these hospitals. Then, the areas where large number of people gathers in Orlando are identified, and these places are predefined as mass casualty disaster locations. For each disaster location, we estimate the potential number of visitors per day, and the distance between each of these locations and the hospitals located in the Orlando area. The data collected in this chapter is used in Chapter 5 to establish an objective function and the restrictions needed (e.g. capacity, age of survivors, and type of hospitals), identifying the optimal hospital networks for each hospital and disaster location identified in Chapter 3.

4.1 Hospitals

The data set includes hospitals' features, such as: hospitals names, longitude, latitude, address, bed-capacity, ED bed capacity and the distance between each hospital and disaster locations. Table 9 displays hospital's names, geographical location, address, owner, and county. It is important to note that in the county column, we include the word *Net*, if the hospital is part of the emergency medical services communications plan.[27] Table 9 lists 15 out of 19 hospitals in different locations within Orlando area. Figure 6 presents the distribution of the hospitals through the Orlando area, which are identified by their short name.

[27] Department of Management Services (DMS) of the State of Florida(2008) "The Emergency Medical Services Communications Plan (EMSCP)" Volume II

Table 9: Location Hospitals

	Full Name	Short Name	Long. (X)	Lat. (Y)	Owner	Address	County
H1	Florida Hospital Orlando	FHO	-81.4	28.6	Florida Hospital	601 East Rollins Street*	Orange - Net
H2	Florida Hospital for Children [2]	FHC	-81.4	28.6	Florida Hospital	601 East Rollins Street*	Orange
H3	Florida Hospital Apopka	FHA	-81.5	28.7	Florida Hospital	North Park Av.	Orange - Net
H4	Florida Hospital East Orlando	FHEO	-81.3	28.5	Florida Hospital	7727 Lake Underhill Rd.	Orange - Net
H5	Winter Park Memorial Hospital	WPMH	-81.3	28.6	Florida Hospital	200 N. Lakemont Av.	Orange-Net
H6	Orlando Regional Medical Center	ORMC	-81.4	28.5	Orlando Regional	1414 Kuhl Avenue*	Orange - Net
H7	M. D. Anderson Cancer Center Orlando	MDACCO	-81.4	28.5	Orlando Regional	1414 Kuhl Avenue*	Orange
H8	Winnie Palmer Hospital for Women & Babies	WPHWB	-81.4	28.5	Orlando Regional	1414 Kuhl Avenue*	Orange
H9	Arnold Palmer Hospital for Children	APHC	-81.4	28.5	Orlando Regional	1414 Kuhl Avenue*	Orange - Net
H10	Dr. P. Phillips Hospital	DPPH	-81.5	28.4	Orlando Regional	9400 Turkey Lake Road	Orange - Net
H11	Orlando Regional Lucerne Hospital	LH	-81.4	28.5	Orlando Regional	818 Main Lane	Orange
H12	South Seminole Hospital	SSH	-81.4	28.7	Orlando Regional	555 W State Road 434	Seminole Net
H13	Nemours Children's Clinic Hospital	NCCH	-81.3	28.4	Nemours	13535 Nemours Parkway	Orange
H14	Health Central	HC	-81.5	28.5	Orlando Regional	10000 West Colonial Drive	Orange - Net
H15	South Lake hospital	SLH	-81.7	28.6	Orlando Regional	1900 Don Wickham Drive	Lake -Net
H16	Florida Hospital Celebration Health	FHCH	-81.5	28.3	Florida Hospital	400 Celebration Place	Osceola - Net
H17	Central Florida Regional Hospital	CFRH	-81.3	28.8	Hospital Corporation of America -HCA Holdings Inc	1401 West Seminole Blvd,	Seminole - Net
H18	Florida Hospital Waterman	FHW	-81.7	28.8	Florida Hospital	1000 Waterman Way	Lake -Net
H19	St. Cloud Regional Medical Center	SCRMC	-81.3	28.2	Orlando Regional	2906 17th Street	Osceola - Net

*: co-located hospitals

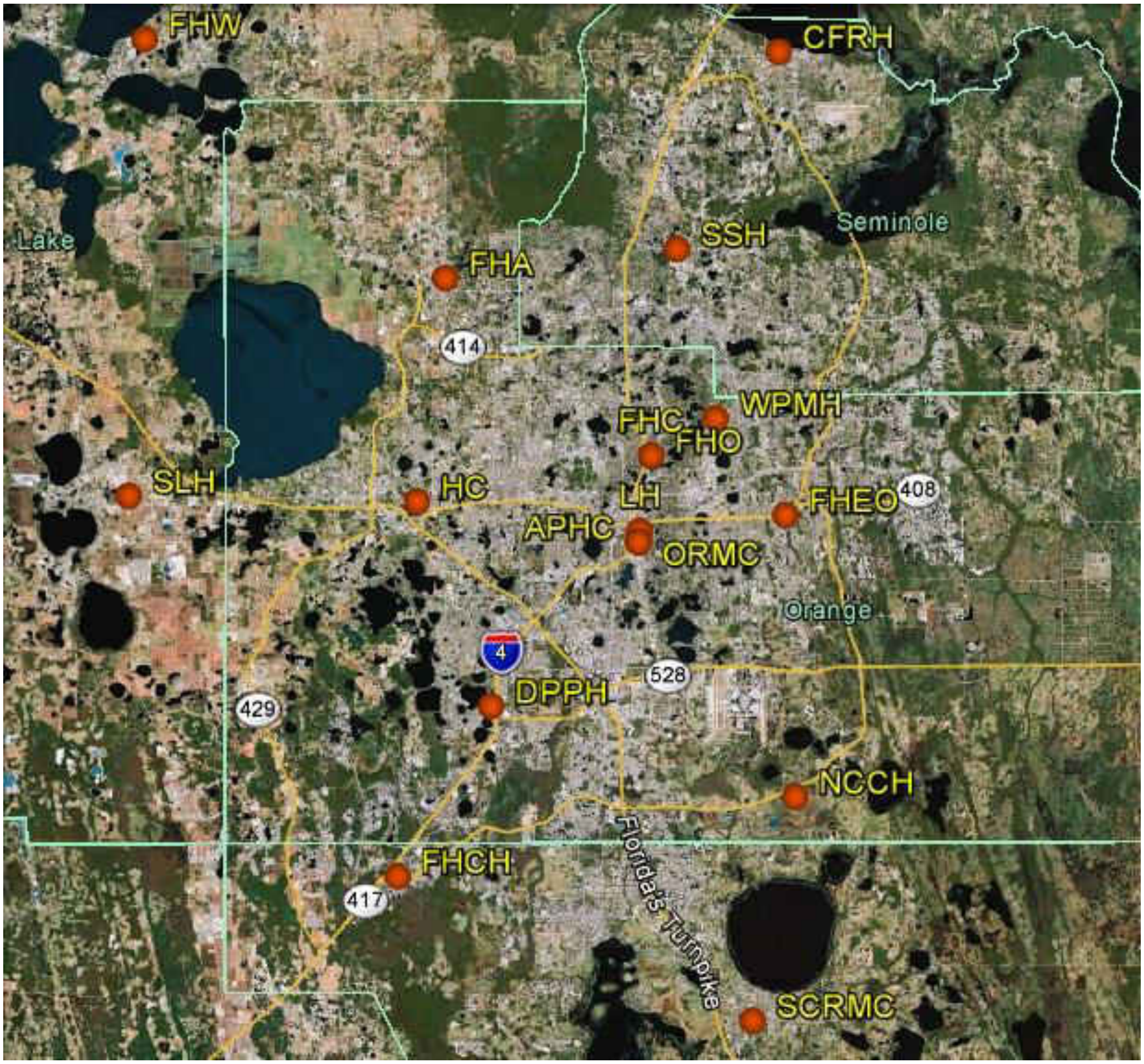

Figure 6: Hospitals Located around Orlando City.

Through an exhaustive exploration, using Google search, we obtained the bed capacities for each hospital. Table 10 shows the total bed capacities reported by each hospital and the total emergency department (ED) bed capacity found in different WebPages, which are specified on the last column. There are two hospitals that do not have an Emergency Department (Orlando Regional Lucerne Hospital and M. D. Anderson Cancer Center Orlando), and the Nemours Children's Clinic Hospital does not publish their availability online because it was not open yet.

Table 10: Hospital Bed-Capacity

	Full Name	Bed Capacity		Source accessed between March 2012 and July 2012
		Total	ED	
1	Arnold Palmer Hospital for Children	158	33	http://www.orlandohealth.com/arnoldpalmerhospital/AboutUs/AboutUs.aspx?pid=2608 http://orlandohealth.com/orlandohealth/ForMedicalProfessionals/Training.aspx?pid=5475
2	Central Florida Regional Hospital	226	48	http://www.centralfloridaregional.com/
3	Dr. P. Phillips Hospital	237	44	http://orlandohealth.com/drpphillipshospital/Welcome/Welcome.aspx?pid=3225 http://orlandohealth.com/drpphillipshospital/OurMedicalSpecialities/EmergencyandTraumaCare.aspx?pid=3168
4	Florida Hospital Apopka	50	16	http://www.floridahospitalnews.com/campus-fact-sheets http://www.linkedin.com/jobs/jobs-Assistant-Nurse-Manager-3001403
5	Florida Hospital Celebration Health	172	28	http://www.celebrationhealth.com/about-us http://www.chooseosceola.com/economicdevelopment/232-130-147/florida_hospital_celebration_health.cfm
6	Florida Hospital East Orlando	224	37	http://www.floridahospitalnews.com/campus-fact-sheets http://www.floridaep.com/facilityprofile.php?id=4
7	Florida Hospital for Children [2]	200	16	http://www.floridahospitalnews.com/campus-fact-sheets http://www.floridahospital.com/blog/pediatric-emergency-department-offers-different-experience-patients-and-families
8	Florida Hospital Orlando	1,080	72	http://www.floridahospitalnews.com/campus-fact-sheets http://www.jobs.net/jobs/adventisthealthsystem/job/emergency-department-registered-nurse-night-shift-10k/J3G5XY6G5KF0KDZ3M5L/
9	Florida Hospital Waterman	204	35	http://www.floridahospital.com/AboutUs/AboutOurCampuses/OtherFloridaHospitalLocations/FloridaHospitalWaterman.aspx http://floridaep.com/facilityprofile.php?id=8
10	Health Central	171	34	http://www.healthcentral.org/about-us/history/ http://www.wotimes.com/articles/2012/03/29/news/top_stories/news01.txt
11	M. D. Anderson Cancer Center Orlando	60		http://www.orlandohealth.com/mdanderson/AboutUs/AboutUs.aspx?pid=2545 http://orlandohealth.com/orlandohealth/ForMedicalProfessionals/Training.aspx?pid=5475
12	Nemours Children's Clinic Hospital	95	N/A	http://www.nemours.org/about/location/nchorlando.html
13	Orlando Regional Lucerne Hospital	267		http://www.hospitalsworldwide.com/listings/1004.php
14	Orlando Regional Medical Center	808	58	http://www.orlandohealth.com/orlandoregionalmedicalcenter/AboutUs/AboutUs.aspx?pid=2685 http://orlandohealth.com/orlandoregionalmedicalcenter/EmergencyCare/EmergencyCare.aspx?pid=3081
15	South Lake hospital	100	30	http://www.southlakehospital.com/AboutUs/tabid/56/Default.aspx http://www.dailycommercialonline.com/specialsections/slpwelcomeback06/pdfs/4.pdf
16	South Seminole Hospital	206	30	http://www.orlandohealth.com/southseminolehospital/AboutUs/AboutUs.aspx?pid=2684 http://articles.orlandosentinel.com/keyword/seminole-hospital
17	St. Cloud Regional Medical Center	84	16	http://www.stcloudregional.com/Careers/WhySCRMC/default.aspx http://www.stcloudregional.com/Services/Emergency-Services/Default.aspx
18	Winnie Palmer Hospital for Women & Babies	285	30	http://www.orlandohealth.com/winniepalmerhospital/AboutUs/AboutUs.aspx?pid=2576 http://orlandohealth.com/orlandohealth/ForMedicalProfessionals/Training.aspx?pid=5475
19	Winter Park Memorial Hospital	297	26	http://www.floridahospitalnews.com/campus-fact-sheets http://www.careerbuilder.com/JobSeeker/Jobs/JobDetails.aspx?job_did=JB75J96C65BXJCKRSPT

As a result, the number of hospitals that have different locations and Emergency Department are only thirteen in Orlando Area. According to GAO (2009), the analysis of the NCHS data indicates that 53 percent of the patients visiting an ED need attention in less than 1 hour, according to acuity level classification[28] (see Figure 7). The optimization problem presented in Chapter 5 uses this 53 percent as a parameter to estimate the available capacity in the ED.

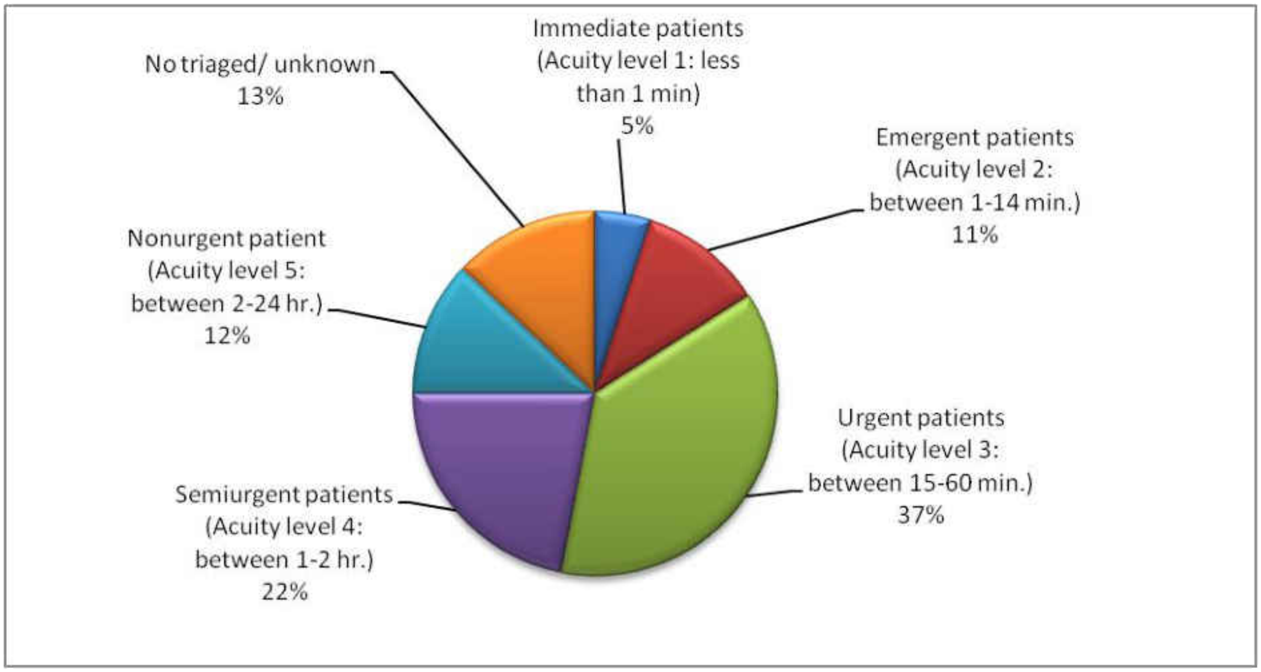

Figure 7: Percentage of ED Visits by Acuity Level

The distances among hospitals were calculated using the Google maps website[29]. This tool provides alternative routes, distances (miles), and travel time duration (minutes). Table 11 depicts the maximum distance in miles among the hospitals studied.[30]

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[28] The acuity classification defines five-level based on emergency severity index recommended by the Emergency Nurses Association. These acuity levels specify the recommended amount of time a patient should wait for a physician. Smaller acuity levels indicate a greater need for fast medical attention.
[29] Google map website available at https://maps.google.com/maps?hl=en (accessed on February 7, 2012)
[30] See appendix A for more data regarding distance and time needed to reach each hospital from another.

Table 11: Maximum Distance between Hospitals (miles)

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19
H1	0	0	16.3	10.6	5.8	5.7	5.7	5.7	5.7	14.1	5.2	12.4	26.1	14	31.4	23.7	22.5	37.4	29.7
H2	0	0	16.3	10.6	5.8	5.7	5.7	5.7	5.7	14.1	5.2	12.4	26.1	14	31.4	23.7	22.5	37.4	29.7
H3	15.5	15.5	0	24.9	18.3	19	19	19	19	28	18.4	13.2	45.8	13.8	25	38	28.4	22.7	44
H4	9.3	9.3	23.1	0	7.9	7.3	7.3	7.3	7.3	20.4	6.8	20.5	16.4	21.5	40.8	36	24.7	52.4	38.2
H5	5.3	5.3	17.4	7.9	0	9.5	9.5	9.5	9.5	18.6	8.9	12.2	24.4	18.9	34.8	28.5	24.1	39	34.5
H6	5.2	5.2	18.9	7	8.9	0	0	0	0	10.5	1.1	16.7	22.4	16.8	33.3	23.9	28.9	43.4	26.6
H7	5.2	5.2	18.9	7	8.9	0	0	0	0	10.5	1.1	16.7	22.4	16.8	33.3	23.9	28.9	43.4	26.6
H8	5.2	5.2	18.9	7	8.9	0	0	0	0	10.5	1.1	16.7	22.4	16.8	33.3	23.9	28.9	43.4	26.6
H9	5.2	5.2	18.9	7	8.9	0	0	0	0	10.5	1.1	16.7	22.4	16.8	33.3	23.9	28.9	43.4	26.6
H10	15.7	15.7	26.3	21	19.1	13.1	13.1	13.1	13.1	0	11	25.8	20.4	15.3	33.2	11	45.8	47.9	25.1
H11	4.1	4.1	17.6	6.3	7.6	0.7	0.7	0.7	0.7	11.8	0	15.4	21.9	17.2	30.3	26.5	28.3	40.4	27
H12	11.4	11.4	12.4	20.8	12.1	16.9	16.9	16.9	16.9	26	16.3	0	36.4	25.3	39.7	35	16.8	36.3	41
H13	25	25	44.8	16.6	24.2	23	23	23	23	20.3	22.4	33.3	0	34	45.4	21	46.5	62.9	18.2
H14	14	14	13.8	21.5	18.9	16.8	16.8	16.8	16.8	15.3	17.2	25.3	34	0	15.5	29.5	37.4	36.7	35.6
H15	31.4	31.4	25	40.8	34.8	33.3	33.3	33.3	33.3	33.2	30.3	39.7	45.4	15.5	0	37.2	52.7	24.9	45.7
H16	23.7	23.7	38	36	28.5	23.9	23.9	23.9	23.9	11	26.5	35	21	25.3	35.7	0	53.2	51.5	23.1
H17	22.5	22.5	28.4	24.7	24.1	28.9	28.9	28.9	28.9	45.8	28.3	16.8	46.5	39.4	53.8	50.2	0	30.2	56.2
H18	37.4	37.4	22.7	52.4	39	43.4	43.4	43.4	43.4	47.9	40.4	36.3	62.9	36.1	27.6	58	47.2	0	71.3
H19	29.7	29.7	44	38.2	34.5	26.6	26.6	26.6	26.6	25.1	27	41	18.2	31.9	46.7	20.2	55.4	62.8	0

4.2 Potential Disaster Locations

The potential locations for mass casualty disasters were established based on the number of people gathered in specific areas, such as theme parks and stadiums. Table 12 shows the names and geographical positions that fit this condition of potential locations for mass casualty disasters in Orlando area. Table 13 captures the statistics on the number of people that are expected at each location. Most of the potential disaster locations are along I-4 (see Figure 8).

Table 12: Location of Potential Disasters

	Full Name	**Short Name**	**Long.**	**Lat.**	**Street**	**Zip Code**	**County**
L1	Airport	AP	-81.3	28.4	1 Airport Blvd	32827	Orange
L2	Amway Center	AC	-81.4	28.5	400 West Church Street	32805	Orange
L3	Animal Kingdom	AK	-81.6	28.4	Bay Lake	32830	Orange
L4	Disney's Hollywood Studios	HST	-81.6	28.4	351 South Studio Dr	32830	Orange
L5	Epcot	EP	-81.5	28.4	200 Epcot Center Drive	32830	Orange
L6	Florida Citrus Bowl Stadium	FCBS	-81.4	28.5	1610 West Church Street	32805	Orange
L7	Florida Mall	FM	-81.4	28.4	8001 S Orange Blossom Tr.	32809	Orange
L8	Magic Kingdom	MK	-81.6	28.4	1180 Seven Seas Drive	32830	Orange
L9	Mall at Millennia	MM	-81.4	28.5	4200 Conroy Road	32839	Orange
L10	Orange County Convention Center	OCCC	-81.5	28.4	9800 International Dr.	32869	Orange
L11	SeaWorld	SW	-81.5	28.4	7007 Sea Harbor Dr.	32821	Orange
L12	Universal	UV	-81.5	28.5	1000 Universal Blvd.	32819	Orange

Table 13: Estimation of the Number of People in Each Location

#	Full Name	Short Name	Capacity Max or total visitors	Unit	Visitors per day	Ratio[31]	Source Accessed between January and March 2012
L1	Airport	AP	70,000	Day	70,000	4.6	http://www.orlandoairports.net/statistics/
L2	Amway Center	AC	17,248	Capacity	17,248	1.1	http://www.amwaycenter.com/
L3	Animal Kingdom	AK	9,590,000	Year	26,274	1.7	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf
L4	Disney's Hollywood Studios	HST	9,700,000	Year	26,575	1.8	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf
L5	Epcot	EP	10,990,000	Year	30,110	2.0	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf
L6	Florida Citrus Bowl Stadium	FCBS	70,000	Capacity	70,000	4.6	http://www.orlandovenues.net/other_info_files/faq_citrus.php
L7	Florida Mall	FM	12,960,000	Year	35,507	2.3	http://www.youtube.com/watch?v=mWq_kbyPOrE
L8	Magic Kingdom	MK	17,233,000	Year	47,214	3.1	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf
L9	Mall at Millenia	MM	10,000,000	Year	27,397	1.8	http://www.mallatmillenia.com/media-press/press-releases/2011/mall-millenia-your-service
L10	Orange County Convention Center	OCCC	24,480	Capacity	24,480	1.6	http://www.occc.net/
L11	SeaWorld	SW	5,800,000	Year	15,890	1.0	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf
L12	Universal	UV	5,530,000	Year	15,151	1.0	http://www.inparkmagazine.com/issues/2009%20Theme%20Index%20Final%20webres.pdf

[31] The column ratio represents the ratio between Visitors per day/ Visitors per day of Universal studios. We use this ratio to define the radius of the circles that represent the disaster location in Figure 8. This radius represents the amount of potential people placed in each of the disaster location.

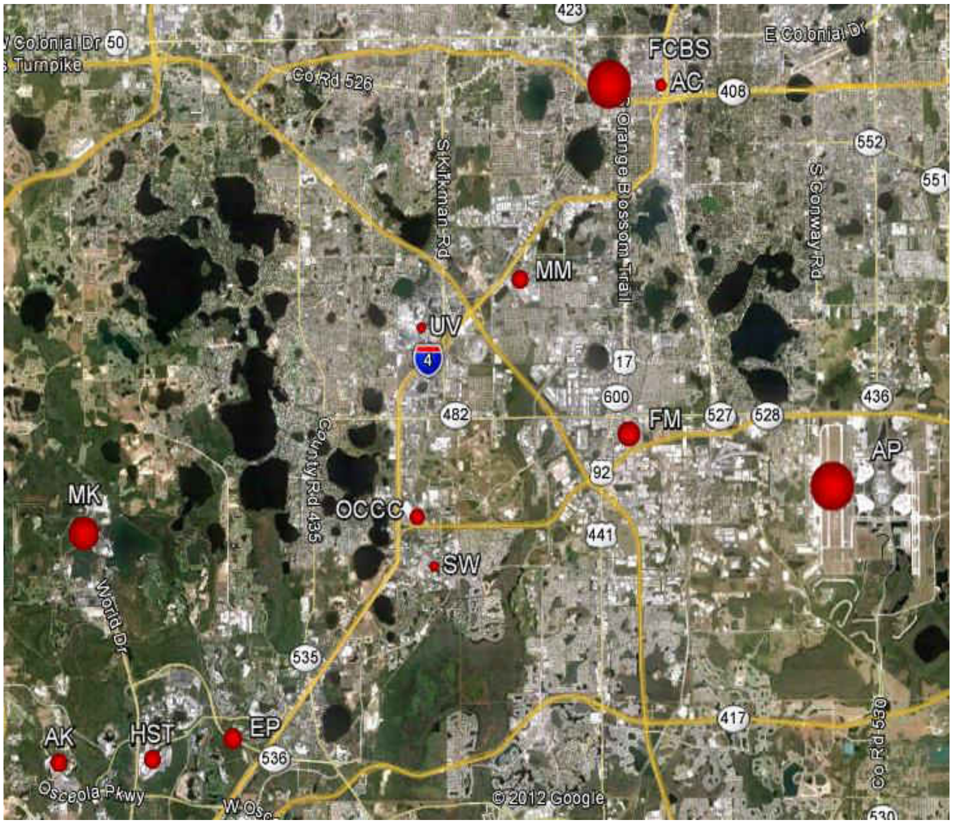

Figure 8: Location of Potential Mass Casualty Disasters

The distances between the potential disasters locations and hospitals were calculated using the Google maps website. This tool provides alternatives routes, distance (miles), and travel time duration (minutes). Table 14 indicates the maximum distance in miles between a disaster location and a hospital[32].

[32] See appendix B for more data regarding distance and time needed to reach each hospital from a potential location disaster.

Table 14: Maximum Distances between Hospitals and Potential Disaster Locations

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
H1	3.7	15.4	28.5	23.1	23.2	4.7	12.6	28.3	10.4	15.8	15.9	12.7
H2	3.7	15.4	28.5	23.1	23.2	4.7	12.6	28.3	10.4	15.8	15.9	12.7
H3	16.6	34.2	23.6	34.7	34.9	15.4	27.5	35.5	23.3	26.3	28.3	23.6
H4	7.9	9.7	31.8	27.8	27.9	7.9	14.3	33	13.2	19	19.5	16.9
H5	7.7	13.7	32	27.6	27.7	8.9	15.1	31.9	13.1	19.4	20.4	15.6
H6	7.7	10.8	25.1	23.3	23.5	4.3	7.7	25	6.2	10.7	14.3	8
H7	7.7	10.8	25.1	23.3	23.5	4.3	7.7	25	6.2	10.7	14.3	8
H8	7.7	10.8	25.1	23.3	23.5	4.3	7.7	25	6.2	10.7	14.3	8
H9	7.7	10.8	25.1	23.3	23.5	4.3	7.7	25	6.2	10.7	14.3	8
H10	11	18.7	15.1	11.1	11.9	10.7	12.1	15.9	6.9	4.4	2.6	3.8
H11	1.2	11.7	25.4	23.7	20.2	2.1	8	25.2	6.3	26	13	8.3
H12	14.2	31.5	39.6	34.2	34.4	15.4	22.5	39.5	20.9	27	40.7	23.6
H13	23.4	13.1	26.4	25.2	25.3	25.7	27	26.9	23.4	22.5	22.3	23.7
H14	11.3	24.4	13.2	24.4	24.5	9.1	19.7	14.2	13.2	15.4	19.7	12.9
H15	28.7	40.2	25	35.7	38.5	28.4	33.6	31	29.3	34.6	33.8	29
H16	21	22.5	12.8	8.8	8.7	20.7	17.4	12.7	16.6	15.2	10.8	13.6
H17	29.6	34.5	58	52.6	52.8	29.5	38.8	57.9	33.8	43.9	43.6	36.3
H18	41	56.4	45.5	51	51.1	38.7	49.7	52.7	45.5	48	43.6	45.2
H19	27	24.7	30.7	23.8	23.9	26.7	20.2	30.5	45.5	20.8	43.6	25.2

4.3 Building Scenarios

The design of scenarios takes emergency departments' capacities, disaster locations, and visitors on the main potential disaster locations in Orlando area[33] into consideration. In this research, we use the GAO's (2009) classification of the Emergency Department visitors to estimate the total capacity of the ED in Orlando. As a result, there are 16 hospitals with ED in Orlando, and considering a 47 percent of available ED beds in adults and children hospitals; we can estimate a capacity of 253 ED beds (see Table 15).

To compute the services offered in each hospital, we followed the Janosikova's (2009) definition for complexity of the hospital. [34] Table 15 displays the average waiting time of each ED in the Orlando area, which was taken from hospital WebPages.

[33] As an additional information, the Orlando January 2012's hospital drill included 256 people acting as victims (annual exercise to coordinate hospitals in the Orlando area)

[34] Complexity of the hospitals – the ability of hospitals to provide urgent health care. The author defines hospitals providing urgent health care need to have at least the following department: surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics. Complexity factor is the ration between the number of services and six.

Table 15: Summary of the Data Used in Each Scenario

	Hospital Name	Available Capacity (ED bed capacity * 0.47)	Average Services	ED Waiting Time
1	Arnold Palmer Hospital for Children	15	1.00	14
2	Central Florida Regional Hospital	22	0.83	12
3	Dr. P. Phillips Hospital	20	0.83	21
4	Florida Hospital Apopka	7	1.00	42
5	Florida Hospital East Orlando	17	0.83	27
6	Florida Hospital for Children	7	0.83	30
7	Florida Hospital Orlando	33	1.00	60
8	Florida Hospital Waterman	16	0.67	12
9	Health Central	15	0.83	25
10	Hospital Celebration health	13	0.67	49
11	M. D. Anderson Cancer Center Orlando	0	0.50	100
12	Nemours Children's Clinic Hospital	0	0.83	100
13	Orlando Regional Lucerne Hospital	0		100
14	Orlando Regional Medical Center	27	0.83	56
15	South Lake Hospital	14	0.67	18
16	South Seminole Hospital	14	0.67	18
17	St. Cloud Regional Medical Center	7	0.67	16
18	Winnie Palmer Hospital	14	0.83	14
19	Winter Park Memorial Hospital	12	0.67	11

Table 16 shows the sizes of the disasters used to create pseudo-optimal networks and the number of pseudo-optimal networks for each scenario. In addition, this work considers two types of victims: children and adults. The Agency for Healthcare Research and Quality indicates that children are not small adults, and they are the most vulnerable patients in terrorism and disasters. [35] In this study, the scenarios consider that twenty percent of the victims are children who are

[35] American Academy of Pediatrics. Pediatric Terrorism and Disaster Preparedness: A Resource for Pediatricians. Foltin GL, Schonfeld DJ, Shannon MW, editors. AHRQ Publication No. 06(07)- 0056. Rockville, MD: Agency for Healthcare Research and Quality. October 2006.

less than fourteen years old. This percentage represents the distribution of the children's population in Orlando, according to the U.S. census 2010.[36]

Table 16: Scenario Features

Disaster size	Victims	Number of Hospital - Hospital Networks (Hub-Hospital Networks)	Number of Disaster Locations - Hospital Networks (Hub-Disaster's Location Networks)-	Total
Small	50	13	12	25
Medium	150	13	12	25
Large	250	13	12	25

[36] Zip-codes.com http://www.zip-codes.com/city/ok-orlando-2010-census.asp (accessed on July 15, 2012)

CHAPTER FIVE: NETWORK OPTIMIZATION

This chapter uses the data collected and processed in Chapter 4 to solve two independent network optimization problems, which minimize the travel distances among hospitals, and minimize the travel distance between hospitals and the disaster locations. The first network optimization model seeks to build different networks, minimizing the travel distance among hospitals with the constraint of allocating victims according to: bed capacity, age of the victim, available services at the hospital, and waiting time in the emergency department. It is essential to reduce the travel distance between hospitals in order to identify possible hospital clusters in case of a disaster occurrence. This identification is important because it will help emergency managers to develop policies regarding the transference of patients (stabilized victims or patients to create surge capacity), or the allocation of more medical resources in hospitals that can become a hub in the network.

The second network optimization model seeks to build hospital networks, minimizing the travel distance between hospitals and disaster locations with the constraints of allocating victims according to: bed capacity, age of the victim, available services at the hospital, and waiting time in the emergency department. This optimization identifies the closest hospitals to the predefined disaster locations, improving the emergency plans designed by the emergency managers of the potential disaster-locations in the Orlando area.

Thus, this chapter begins describing both optimization models and their results. Then, the result sections of this chapter display the estimations of average distance, average waiting time, and average services for every pseudo-optimal network for each optimization model. Finally, the analyzed results are grouped according to the size of the disaster. The data gathered for each hospital network will feed the data envelopment analysis performed in Chapter 6 in order to identify the efficiency index for each hospital network established in this chapter.

5.1 Minimizing the Travel Distances among Hospitals

The network is a graph in which each node "h" of the set of nodes "N" represents hospitals, and the node "l" represents the hub hospital. Then, each arc (l,h) of the set of arcs "A" represents the distance d_{lh} between hub hospital "l" and hospital "h". The inclusion of hospitals into a network responds to the following characteristics: (1) the distances between the hub hospital and the rest of the hospitals, (2) the average number of services, (3) the average waiting time in the ED, and (4) the available capacity in their ED. Three different disaster sizes define three-pseudo optimal hospital networks for each one of the thirteen hospitals in the Orlando area.

5.1.1 Model

In this model, the variable X_{lh} represents the number of the victims transported from the hub-hospital "l" to hospital "h". If X_{lh} is larger than zero, then the hospital "h" is part of the pseudo-optimal network. Nineteen hospitals -four hospitals for children and 15 hospitals for adults- can be part of the pseudo-optimal network. However, only 13 hospitals can be hub-hospitals because the remaining hospitals do not have ED or present co-locations features, as Table 9 and Table 15 display. For each predefined hub-hospital l, a mathematical programming model identifies the pseudo-optimal hospital network, once the hub-hospital l is included in the network.

In order to explain the mathematical model, the description of constraints is the following: The equation (5.1) defines the number of victims transported to the children's hospital (i) and the adult's hospital (j) must be equal to the number of victims in hospital l, and

$$\sum_i^4 X_{li} + \sum_j^{15} X_{lj} = V_l \tag{5.1}$$

The equation (5.2) states that the number of children transported to the children's hospitals (i) must be less or equal to the percentage of children victims (patients) at the disaster.

$$\sum_i^4 \mathrm{X}_{\mathrm{li}} \leq \mathrm{PofC} * \mathrm{V}_{\mathrm{l}} \tag{5.2}$$

In addition, the following constraints (5.3) and (5.4) limit the number of adult victims and children victims transported to the adult's hospitals and children hospitals respectively, according to the available capacity in the emergency department of those hospitals.

$$\mathrm{X}_{\mathrm{lj}} \leq \mathrm{FCP} * \mathrm{C}_{\mathrm{j}} \tag{5.3}$$

$$\mathrm{X}_{\mathrm{li}} \leq \mathrm{FCP} * \mathrm{C}_{\mathrm{i}} \tag{5.4}$$

The first objective (5.5) of the design of the network seeks to minimize the distance that victims need to travel to reach a hospital from the hub.

$$\text{Minimize } \mathrm{f}_1(X) = \sum_h^{19} d_{1h} X_{lh} \tag{5.5}$$

The second objective (5.6) is to include hospitals, which provide more services.

$$\text{Maximize } \mathrm{f}_2(X) = \sum_h^{19} s_h X_{1h} \tag{5.6}$$

The third objective (5.7) is the allocation of children into the children' hospitals as a priority.

$$\text{Minimize } \mathrm{f}_3(X) = \sum_i^4 C_i - \sum_i^4 X_{li} \tag{5.7}$$

The fourth objective (5.8) seeks to include in the network, hospitals that present the least ED waiting time.

Minimize $f_4(X) = \sum_i^4 WTC_i X_{li} + \sum_j^{15} WTA_j X_{lj}$ (5.8)

Then, the problem to resolve has multiple objectives,

Min $Z = \sum_h^{19} d_{1h} X_{lh} - 30 \sum_h^{19} s_h X_{1h} + V_l(\sum_i^4 C_i - \sum_i^4 X_{li}) + \left(\sum_i^4 WTC_i X_{li} + \sum_j^{15} WTA_j X_{lj}\right)/V_l$

Subject to:

$\sum_i^4 X_{li} + \sum_j^{15} X_{lj} = V_l$

$\sum_i^4 X_{li} \leq \text{PofC} * \text{V}_\text{l}$

$X_{lj} \leq \text{FCP} * \text{C}_\text{j}$

$X_{li} \leq \text{FCP} * \text{C}_\text{i}$

$X_{li} \geq 0$

Where:

h: hospital in Orlando area (1,..., 19)

l: hub hospital (1,..., 13)

i: children's hospital (1,...,4)

j: adult's hospital (1,...,15)

X_{lh}: number of victims transported from hub hospital l to hospital h

d_{1h}: distance from hub hospital l to hospital h

s_h: average services in hospital h

V_1: victims (patients) in hub hospital l

C_h: capacity Emergency Department in hospital h

Cj: Adult bed capacity in hospital j

Ci: Children bed capacity in hospital i

WTC_i: waiting time in children's hospital i

WTA_j: waiting time in adult's hospital j

PofC: Percentage of children (0.2)

FCP: Free Capacity Percentage in Emergency Department (0.47)

5.1.2 Results

The optimization problem described in Section 5.1.1 identifies a pseudo-optimal network for each predefined hub-hospital in the Orlando area for each predefined disaster size. The distances from each hub-hospital to the rest of the hospitals change in each case to define the pseudo-optimal networks. This research uses AIMMS® to implement the optimization model (see Appendix C). Table 17 displays: the number of victims, hospitals, and children allocated in hospitals for adults. In addition, we compute for each network the following features: (i) the average distance between the hub-hospital and the rest of the hospitals in the network; (ii) the average services offered for hospitals in the network, and (iii) the average waiting time measured in minutes.

For instance, the first row is read as follows: Florida Hospital Orlando is the hub hospital from where are distributed 50 patient or victims to other 3 hospitals, which are located within 1.16 miles range. The hub-hospital and the other 3 hospitals offer in overall an average 0.94 services of out of 1 services-ratio[37]. These four hospitals present that a patient has to wait in the emergency department an average of 46.18 minutes before they could receive medical care. In this network, there are not children are assigned to an adult's hospital. Then, the last row can be read, as follow: St. Cloud Regional Medical Center is the hub hospital from where are distributed 250 patient or victims to other 15 hospitals, which are located within 34.22 miles range. The hub-hospital and the other 15 hospitals offer in overall an average 0.82 services of out of 1 services-ratio. These four hospitals present that a patient has to wait in the emergency

[37] The services variable follows the Janosikova (2009) criterion for measuring quality of the networks. This criterion includes the following services: surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics. In order to determine the services available in the network, we search for all these services offered in hospitals, and then, we calculate the average of these services.

department an average of 29.844 minutes before they could receive medical care. In this network, there are 14 children are assigned to an adult's hospital.

Table 17: Results for each Hub-Hospital

	Hub-Hospital Name	**# Victims**	**# Hospitals**	**Avge. Distance**	**Avge. Services**	**Avge. Waiting Time**	**# Children**
1	Florida Hospital Orlando	50	4	1.162	0.940	46.180	0
2	Florida Hospital Apopka	50	6	12.388	0.840	28.260	0
3	Florida Hospital East Orlando	50	4	4.966	0.820	26.940	0
4	Winter Park Memorial Hospital	50	4	4.282	0.900	41.280	0
5	Orlando Regional Medical Center	50	3	1.360	0.900	48.640	0
6	Dr. P. Phillips Hospital	50	4	7.318	0.820	31.780	0
7	South Seminole Hospital	50	4	8.540	0.880	39.320	0
8	Health Central	50	5	9.942	0.920	40.020	0
9	South Lake Hospital	50	5	16.524	0.760	20.220	0
10	Florida Hospital Celebration	50	4	12.416	0.800	26.180	0
11	Central Florida Regional Hospital	50	5	11.392	0.800	20.160	0
12	Florida Hospital Waterman	50	6	20.916	0.760	21.300	0
13	St Cloud Regional Medical Center	50	4	20.614	0.800	26.180	0
14	Florida Hospital Orlando	150	10	6.313	0.860	35.227	0
15	Florida Hospital Apopka	150	10	16.359	0.853	34.807	0
16	Florida Hospital East Orlando	150	9	9.690	0.860	34.247	0
17	Winter Park Memorial Hospital	150	10	8.667	0.867	35.807	0
18	Orlando Regional Medical Center	150	9	5.320	0.873	34.760	0
19	Dr. P. Phillips Hospital	150	9	12.462	0.860	36.813	0
20	South Seminole Hospital	150	10	13.378	0.867	33.353	0
21	Health Central	150	10	13.969	0.873	36.060	0
22	South Lake Hospital	150	10	26.607	0.860	32.567	0
23	Florida Hospital Celebration	150	10	20.312	0.860	37.487	0
24	Central Florida Regional Hospital	150	11	20.467	0.847	28.140	0
25	Florida Hospital Waterman	150	11	32.987	0.833	30.087	0
26	St Cloud Regional Medical Center	150	10	26.101	0.860	36.847	0

	Hub-Hospital Name	# Victims	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	# Children
27	Florida Hospital Orlando	250	16	13.144	0.820	29.844	14
28	Florida Hospital Apopka	250	16	21.147	0.820	29.796	14
29	Florida Hospital East Orlando	250	16	18.345	0.820	29.956	14
30	Winter Park Memorial Hospital	250	16	15.852	0.820	29.844	14
31	Orlando Regional Medical Center	250	16	13.702	0.820	29.844	14
32	Dr. P. Phillips Hospital	250	16	20.546	0.820	30.684	14
33	South Seminole Hospital	250	16	20.051	0.820	29.404	14
34	Health Central	250	16	19.990	0.820	29.844	14
35	South Lake Hospital	250	16	32.250	0.820	29.844	14
36	Florida Hospital Celebration	250	16	28.369	0.820	29.956	14
37	Central Florida Regional Hospital	250	16	26.342	0.820	29.796	14
38	Florida Hospital Waterman	250	16	38.905	0.820	29.796	14
39	St Cloud Regional Medical Center	250	16	34.221	0.820	29.844	14

In Table 18, Table 19, and Table 20 include two new columns. The first one indicate the average distance from the hub-hospital to the imaginary disaster location that correspond to the average distance from the hub-hospital to the 12 disaster locations identified in this research. We named this column as "*Avge. Dist. from Pot. Disasters*". The second one indicates the number of victims or patients that can be allocated in hospitals within 40 miles range from the hub-hospital. This column is called *"# Victims allocated (less than 40 miles)"*.

For small disasters of 50 victims, according to Table 18, the first seven hospitals can be hub-hospitals for small category because they are near to the twelve potential disaster-locations. In addition, the distance between these hospitals and other hospitals in the Orlando area is small, and it allows the hub-hospital, for small disasters, to reduce the casualties because they can transport the victims to alternative hospitals in a short period. However, the Central Florida Regional Hospital and Florida Hospital Waterman cannot be considered as hub-hospitals for small disasters because their locations are in average further than 40 miles away from the twelve potential disaster-locations identified in Chapter 4.

Table 18: Small Network for each Hub-Hospital

	Hub-Hospital Name	Avge. Dist. from Pot. Disasters	# Hospi tals	Avge. Distance	Avge. Services	Avge. Waitin g Time	# Children Allocated in adult hosp.	# Victims allocated (less than 40 miles)
1	Florida Hospital Orlando	16.2	4	1.16	0.94	46.18	0	50
2	Florida Hospital East Orlando	19.1	4	4.97	0.82	26.94	0	50
3	Winter Park Memorial Hospital	19.4	4	4.28	0.90	41.28	0	50
4	Orlando Regional Medical Center	13.9	3	1.36	0.90	48.64	0	50
5	Dr. P. Phillips Hospital	10.4	4	7.32	0.82	31.78	0	50
6	Health Central	16.8	5	9.94	0.92	40.02	0	50
7	Florida Hospital Celebration	15.1	4	12.42	0.80	26.18	0	50
8	Florida Hospital Apopka	27.0	6	12.39	0.84	28.26	0	21
9	South Seminole Hospital	28.6	4	8.54	0.88	39.32	0	14
10	South Lake Hospital	32.3	5	16.52	0.76	20.22	0	14
11	St Cloud Regional Medical Center	28.6	4	20.61	0.80	26.18	0	7
12	Central Florida Regional Hospital	42.6	5	11.39	0.80	20.16	0	0
13	Florida Hospital Waterman	47.4	6	20.92	0.76	21.30	0	0

Table 19 indicates that for medium disasters the first five hospitals can be hub-hospitals, where 150 victims can be allocated within a 40 miles range. These five hub-hospitals are near to the twelve disaster-locations predefined. In addition, the distance between these five hospitals and other hospitals in the Orlando area is small, and it allows the hub-hospital to reduce the casualties, transporting the victims to alternative hospitals. On the other hand, Central Florida Regional Hospital and Florida Hospital Waterman cannot be hub-hospitals for medium disasters because their locations are in average further than 40 miles away from the twelve potential disaster-locations identified.

Table 19: Medium Network for each Hub-Hospital

	Hub-Hospital Name	Avge. Dist. from Pot. Disasters	# Hospi tals	Avge. Distance	Avge. Services	Avge. Waitin g Time	# Children Allocated in adult hosp.	# Victims allocated (less than 40 miles)
1	Florida Hospital Orlando	16.2	10	6.31	0.86	35.23	0	150
2	Winter Park Memorial Hospital	19.4	10	8.67	0.87	35.81	0	150
3	Orlando Regional Medical Center	13.9	9	5.32	0.87	34.76	0	150
4	Dr. P. Phillips Hospital	10.4	9	12.46	0.86	36.81	0	150
5	Health Central	16.8	10	13.97	0.87	36.06	0	150
6	Florida Hospital East Orlando	19.1	9	9.69	0.86	34.25	0	130
7	Florida Hospital Celebration	15.1	10	20.31	0.86	37.49	0	130
8	Florida Hospital Apopka	27	10	16.36	0.85	34.81	0	21
9	South Seminole Hospital	28.6	10	13.38	0.87	33.35	0	14
10	South Lake Hospital	32.3	10	26.61	0.86	32.57	0	14
11	St Cloud Regional Medical Center	28.6	10	26.1	0.86	36.85	0	7
12	Central Florida Regional Hospital	42.6	11	20.47	0.85	28.14	0	0
13	Florida Hospital Waterman	47.4	11	32.99	0.83	30.09	0	0

There are not pseudo-optimal network for a hub-hospital that allocates 250 victims within a 40 miles range. For this large disaster, according to Table 20, the best alternative is the Florida Hospital Orlando as a hub-hospital, allocating only 216 victims within a 40 miles range. However, Central Florida Regional Hospital and Florida Hospital Waterman cannot be hub-hospitals for large disasters because their locations are in average further than 40 miles away from the twelve potential disaster-locations.

Table 20: Large Network for each Hub-Hospital

		Avge. Dist. from Pot. Disasters	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	# Children Allocated in adult hosp.	# Victims allocated (less than 40 miles)
1	Florida Hospital Orlando	16.2	16	13.14	0.82	29.84	14	216
2	Dr. P. Phillips Hospital	10.4	16	20.55	0.82	30.68	14	201
3	Orlando Regional Medical Center	13.9	16	13.7	0.82	29.84	14	194
4	Winter Park Memorial Hospital	19.4	16	15.85	0.82	29.84	14	181
5	Health Central	16.8	16	19.99	0.82	29.84	14	181
6	Florida Hospital East Orlando	19.1	16	18.34	0.82	29.96	14	139
7	Florida Hospital Celebration	15.1	16	28.37	0.82	29.96	14	136
8	Florida Hospital Apopka	27.0	16	21.15	0.82	29.8	14	21
9	South Seminole Hospital	28.6	16	20.05	0.82	29.4	14	14
10	South Lake Hospital	32.3	16	32.25	0.82	29.84	14	14
11	St Cloud Regional Medical Center	28.6	16	34.22	0.82	29.84	14	7
12	Central Florida Regional Hospital	42.6	16	26.34	0.82	29.8	14	0
13	Florida Hospital Waterman	47.4	16	38.9	0.82	29.8	14	0

Table 21 displays the frequency of each hospital in a pseudo-optimal network, according to the size of the disaster. This table identifies eight hospitals out of sixteen hospitals that fit better within the pseudo-optimal network analyzed previously (Arnold Palmer Hospital for Children, Florida Hospital for Children, Florida Hospital Orlando, Orlando Regional Medical Center, Winnie Palmer Hospital, Winter Park Memorial Hospital, Dr. P. Phillips Hospital, and Health Central). In addition, it is important to notice that hospitals for children are part of most of the pseudo-optimal networks because this optimization model assigns children to hospitals for children as a priority, and if hospitals for children have no capacity, the children are allocated in adult hospitals.

Table 21: Hospital Frequency in Networks

	Hospital Name (Emergency Department)	Small	Medium	Large
1	Arnold Palmer Hospital for Children	13	13	13
2	Florida Hospital for Children	8	13	13
3	Florida Hospital Orlando	7	13	13
4	Orlando Regional Medical Center	3	13	13
5	Winnie Palmer Hospital	0	13	13
6	Winter Park Memorial Hospital	3	12	13
7	Dr. P. Phillips Hospital	3	9	13
8	Health Central	4	9	13
9	Florida Hospital Apopka	3	7	13
10	South Seminole Hospital	3	7	13
11	Florida Hospital East Orlando	1	6	13
12	South Lake Hospital	2	4	13
13	Florida Hospital Waterman	2	3	13
14	Hospital Celebration health	3	3	13
15	Central Florida Regional Hospital	1	2	13
16	St. Cloud Regional Medical Center	2	2	13

5.2 Minimizing Travel Distances between Disaster Locations and Hospitals

The network is a graph in which each node "h" of the set of nodes "N" represents a hospital or disaster location "l". Then, each arc (l,h) of the set of arcs "A" represents the distance d_{lh} between disaster location "l" and hospital "h". The inclusion of hospitals into a network responds to the following features: (i) the distances between the disaster location and the hospitals, (ii) the number of services, (iii) the average waiting time in ED, and (iv) the available capacity in their ED. The three different disaster sizes define three-pseudo optimal hospital networks for each one of the twelve defined disaster locations in the Orlando area.

5.2.1 Model

In this second model, the variable X_{lh} represents the number of the victims transported from the disaster location l to hospital h. If X_{lh} is larger than zero, then the hospital h is included into the pseudo-optimal network. There are nineteen hospitals in the Orlando area, which are classified in four hospitals for children and fifteen hospitals for adults. For each disaster location, a mathematical model identifies the pseudo-optimal hospitals network.

In order to explain the mathematical model, the description of constraints is the following: The equation (5.9) defines the number of victims transported to the children's hospital (i) and the adult's hospital (j) must be equal to the number of victims in the disaster location l, and

$$\sum_i^4 X_{li} + \sum_j^{15} X_{lj} = V_l \tag{5.9}$$

Equation (5.10) states the number of children transported to the children's hospital (i) must be less or equal to the percentage of children victims at the disaster.

$$\sum_i^4 X_{li} \leq \mathrm{PofC} * \mathrm{V_l} \tag{5.10}$$

In addition, the constraints (5.11) and (5.12) limit the number of adult and children victims transported to adult hospitals and children hospitals respectively, according to the available capacity in the emergency department in those hospitals.

$$X_{lj} \leq \mathrm{FCP} * \mathrm{C_j} \tag{5.11}$$

$$X_{li} \leq \mathrm{FCP} * \mathrm{C_i} \tag{5.12}$$

The first objective of the design of the network is to minimize the distance that victims need to travel to reach a hospital from the hub.

Minimize $f_l(X) = \sum_h^{19} d_{1h} X_{lh}$ (5.13)

The second objective is to keep hospitals, which provide more services

Maximize $f_2(X) = \sum_h^{19} s_h X_{1h}$ (5.14)

The third objective is the allocation of children into children's hospitals as a priority

Minimize $f_3(X) = \sum_i^4 C_i - \sum_i^4 X_{li}$ (5.15)

The fourth objective is to include in the network, hospitals that present less waiting time

Minimize $f_4(X) = \sum_i^4 WTC_i X_{li} + \sum_j^{15} WTA_j X_{lj}$ (5.16)

Then, the problem to resolve is multiple objectives,

$$\text{Min } Z = \sum_h^{19} d_{1h} X_{lh} - 30 \sum_h^{19} s_h X_{1h} + V_l\left(\sum_i^4 C_i - \sum_i^4 X_{li}\right) + \left(\sum_i^4 WTC_i X_{li} + \sum_j^{15} WTA_j X_{lj}\right)/V_l$$

Subject to:

$$\sum_i^4 X_{li} + \sum_j^{15} X_{lj} = V_l$$

$$\sum_i^4 X_{li} \leq \text{PofC} * V_l$$

$$X_{lj} \leq \text{FCP} * C_j$$

$$X_{li} \leq \text{FCP} * C_i$$

$$X_{li} \geq 0$$

Where:

h: hospital in Orlando area (1,..., 19)

l: disaster location (1,..., 12)

i: children's hospital (1,...,4)

j: adult's hospital (1,...,15)

X_{lh}: number of victims transported from disaster location l to hospital h

d_{lh}: distance from disaster location l to hospital h

s_h: average services in hospital h

V_l: victims in disaster location l

C_h: capacity Emergency Department in hospital h

Cj: Adult bed capacity in hospital j

Ci: Children bed capacity in hospital i

WTC_i: waiting time in children's hospital i

WTA_j: waiting time in adult's hospital j

PofC: Percentage of children (0.2)

FCP: Free Capacity Percentage (0.47)

5.2.2 Results

The optimization problem described in section 5.2.1 identifies a pseudo-optimal network for each disaster locations identified in the Orlando area. The travel distances from each disaster to hospital the change in each case when is computing the pseudo optimal network for every disaster-location. This research uses AIMMS[38] to implement this optimization model (see appendix C)

Table 22: Results for each Disaster Location

	Disaster - Location	# Victims	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	# Children
1	Airport	50	4	9.052	0.820	18.160	0
2	Amway Center	50	4	12.860	0.820	19.240	0
3	Animal Kingdom	50	4	18.220	0.840	19.800	0
4	Hollywood Studios	50	5	19.544	0.800	16.580	0
5	Epcot	50	5	19.940	0.800	16.580	0
6	Florida Citrus Bowl Stadium	50	4	8.720	0.820	17.840	0
7	Florida Mall	50	5	13.118	0.800	16.620	0
8	Magic Kingdom	50	4	18.810	0.840	19.800	0
9	Mall At Millennia	50	4	9.256	0.820	17.840	0
10	Orange County Convention Center	50	4	11.020	0.820	17.840	0
11	SeaWorld	50	3	12.820	0.860	16.000	0
12	Universal	50	4	8.928	0.820	17.840	0
13	SeaWorld	150	11	24.811	0.938	20.328	0
14	Airport	150	11	15.035	0.800	17.893	0
15	Amway Center	150	11	21.956	0.800	17.893	0

[38] This optimization software includes Linear Programming, Mixed Integer Programming, Nonlinear Programming, Mixed Integer Nonlinear Programming, Robust Optimization, Stochastic Programming, and Advanced Algorithms for Mathematical Programs. An academic version of this software is available at http:/www.aimms.com/academic/free-academic-license (accessed on June 5, 2012)

	Disaster - Location	# Victims	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	# Children
16	Animal Kingdom	150	12	27.429	0.787	19.253	0
17	Hollywood Studios	150	12	25.140	0.780	21.140	0
18	Epcot	150	12	25.605	0.780	21.140	0
19	Florida Citrus Bowl Stadium	150	11	14.278	0.800	17.893	0
20	Florida Mall	150	11	19.630	0.800	17.893	0
21	Magic Kingdom	150	12	26.769	0.773	21.140	0
22	Mall At Millennia	150	11	16.627	0.813	18.947	0
23	Orange County Convention Center	150	11	20.934	0.800	17.893	0
24	Universal	150	11	17.807	0.800	17.893	0
25	Airport	250	16	15.274	0.820	29.400	14
26	Amway Center	250	16	22.368	0.820	29.400	14
27	Animal Kingdom	250	16	29.358	0.820	29.268	14
28	Hollywood Studios	250	16	28.106	0.820	29.316	14
29	Epcot	250	16	28.442	0.820	29.316	14
30	Florida Citrus Bowl Stadium	250	16	13.614	0.820	29.400	14
31	Florida Mall	250	16	19.356	0.820	29.400	14
32	Magic Kingdom	250	16	30.612	0.816	29.268	14
33	Mall At Millennia	250	16	17.211	0.820	29.400	14
34	Orange County Convention Center	250	16	20.728	0.816	29.268	14
35	SeaWorld	250	16	20.712	0.816	29.268	14
36	Universal	250	16	17.754	0.816	29.268	14

Table 23, Table 24, and Table 25 describe these results according to size of the disasters small, medium, and large respectively.

Table 23: Small Network for each Disaster Location

	Disaster-Location	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	#Children Allocated in adult hosp	# Victims allocated (less than 40 miles)
1	Airport	4	9.05	0.82	18.16	0	50
2	Amway Center	4	12.86	0.82	19.24	0	50
3	Animal Kingdom	4	18.22	0.84	19.80	0	50
4	Hollywood Studios	5	19.54	0.80	16.58	0	50
5	Epcot	5	19.94	0.80	16.58	0	50
6	Florida Citrus Bowl Stadium	4	8.72	0.82	17.84	0	50
7	Florida Mall	5	13.12	0.80	16.62	0	50
8	Magic Kingdom	4	18.81	0.84	19.80	0	50
9	Mall At Millennia	4	9.26	0.82	17.84	0	50
10	Orange County Convention Center	4	11.02	0.82	17.84	0	50
11	Universal	4	8.93	0.82	17.84	0	50
12	SeaWorld	3	12.82	0.86	16.00	0	30

According to Table 23, whether a small disaster with 50 victims occurs, eleven out of twelve predefined disaster-locations can allocate 50 victims in the hospitals situated in a radius less than 40 miles. This table also indicates that SeaWorld is the only location from where it is not possible to distribute 50 victims in hospitals located within a 40 miles range, but the victims are allocated in the hospitals with less ED waiting time further than a 40 miles range.

Table 24: Medium Network for each Disaster Location

	Disaster-Locations	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	#Children Allocated in adult hosp	# Victims allocated (less than 40 miles)
1	Airport	11	15.04	0.8	17.89	0	150
2	Florida Citrus Bowl Stadium	11	14.28	0.8	17.89	0	150
3	Florida Mall	11	19.63	0.8	17.89	0	150
4	Mall At Millennia	11	16.63	0.81	18.95	0	150
5	Universal	11	17.81	0.8	17.89	0	150
6	Hollywood Studios	12	25.14	0.78	21.14	0	142
7	Epcot	12	25.6	0.78	21.14	0	142
8	Magic Kingdom	12	26.77	0.77	21.14	0	142
9	Amway Center	11	21.96	0.8	17.89	0	137
10	Animal Kingdom	12	27.43	0.79	19.25	0	134
11	Orange County Convention Center	11	20.93	0.8	17.89	0	128
12	SeaWorld	11	24.81	0.94	20.33	0	108

In the case of a medium size disaster with 150 victims, only five locations out of twelve can allocate 150 victims in hospitals located within a 40 miles range from the disaster (see the first five locations in Table 24). On the other hand, if a medium disaster occurs in Orange County Convention Center or SeaWorld, it is not possible to allocate more than 128 and 108 victims in those hospitals respectively but the victims are allocated in the hospitals with less ED waiting time further than 40 miles away.

Table 25: Large Network for each Disaster Location

	Disaster-Location	# Hospitals	Avge. Distance	Avge. Services	Avge. Waiting Time	#Children Allocated in adult hosp	# Victims allocated (less than 40 miles)
1	Florida Citrus Bowl Stadium	16	13.61	0.82	29.40	14	250
2	Airport	16	15.27	0.82	29.40	14	234
3	Florida Mall	16	19.36	0.82	29.40	14	234
4	Universal	16	17.75	0.82	29.27	14	234
5	Mall At Millennia	16	17.21	0.82	29.40	14	227
6	Amway Center	16	22.37	0.82	29.40	14	220
7	Animal Kingdom	16	29.36	0.82	29.27	14	212
8	Hollywood Studios	16	28.11	0.82	29.32	14	212
9	Epcot	16	28.44	0.82	29.32	14	212
10	Magic Kingdom	16	30.61	0.82	29.27	14	212
11	Orange County Convention Center	16	20.73	0.82	29.27	14	212
12	SeaWorld	16	20.71	0.82	29.27	14	191

In a large disaster considering 250 victims, the Florida Citrus Bowl Stadium is the only disaster locations that allocates 250 victims in hospitals located in a radius of 40 miles. On the other hand, the SeaWorld pseudo-optimal network presents the worse behavior, allocating only 191 victims in hospitals located in the same radius but the victims are allocated in the hospitals with less ED waiting time further than 40 miles away.

Table 26: Hospital Frequency in Networks

	Hospital Name	Disaster Size		
		Small	Medium	Large
1	Arnold Palmer Hospital for Children	12	12	12
2	Dr. P. Phillips Hospital	12	12	12
3	Florida Hospital East Orlando	11	12	12
4	Winter Park Memorial Hospital	11	12	12
5	Central Florida Regional Hospital	1	12	12
6	Florida Hospital for Children	0	12	12
7	South Seminole Hospital	0	12	12
8	Winnie Palmer Hospital	0	12	12
9	St. Cloud Regional Medical Center	6	11	12
10	Florida Hospital Waterman	0	10	12
11	Florida Hospital Apopka	0	7	12
12	Hospital Celebration health	0	5	12
13	Orlando Regional Medical Center	0	5	12
14	Florida Hospital Orlando	0	3	12
15	Health Central	0	0	12
16	South Lake Hospital	0	0	12

Table 26 displays the frequency of each hospital in a pseudo-optimal network, according to the size of the disaster. This table identifies six main hospitals out of sixteen hospitals that fit better within the pseudo-optimal network analyzed previously (Arnold Palmer Hospital for Children, Dr. P. Phillips Hospital, Florida Hospital East Orlando, Winter Park Memorial Hospital, Central Florida Regional Hospital, and St. Cloud Regional Medical Center). In addition, it is important to mention that hospitals for children take part in most of the pseudo-optimal networks because this optimization model assigns children to hospitals for children as a priority, and if hospitals for children have no capacity, the children are assigned to adult hospitals.

5.3 Results Discussion

The results of the two network optimization problems summarized in Table 27 show the frequency of each hospital in a pseudo-optimal network. The first problem is the minimization of distances among hospitals, and the second is the minimization of distances between hospitals and disaster-location. These results highlight that ten out of sixteen hospitals participate in more than 62 percent of the total pseudo-optimal networks generated in previous sections of this chapter. Due to unpredictability of disasters, these ten hospitals should develop joint exercises to improve the response time and efforts in a mass casualty disaster.

Table 27: Summarized Results

	Hospital Name	Hub-hospital Networks			Disaster Location Networks			Total
		Small	Medium	Large	Small	Medium	Large	
1	Arnold Palmer Hospital for Children	13	13	13	12	12	12	75*
2	Dr. P. Phillips Hospital	3	9	13	12	12	12	61*
3	Florida Hospital East Orlando	1	6	13	11	12	12	55*
4	Winter Park Memorial Hospital	3	12	13	11	12	12	63*
5	Central Florida Regional Hospital	1	2	13	1	12	12	41
6	Florida Hospital for Children	8	13	13	0	12	12	58*
7	South Seminole Hospital	3	7	13	0	12	12	47*
8	Winnie Palmer Hospital	0	13	13	0	12	12	50*
9	St. Cloud Regional Medical Center	2	2	13	6	11	12	46*
10	Florida Hospital Waterman	2	3	13	0	10	12	40
11	Florida Hospital Apopka	3	7	13	0	7	12	42
12	Hospital Celebration health	3	3	13	0	5	12	36
13	Orlando Regional Medical Center	3	13	13	0	5	12	46*
14	Florida Hospital Orlando	7	13	13	0	3	12	48*
15	Health Central	4	9	13	0	0	12	38
16	South Lake Hospital	2	4	13	0	0	12	31

*: Hospitals that participate in more than 62% of the total networks.

In addition, a detailed list of the pseudo-optimal network is available in Appendix C.3. Table 28, displays a sample of the 75 optimal networks computed in this chapter. The name in the first column indicates the hub of the network. The second column indicates the number of victims in the disaster site. The remaining columns indicate the hospitals numbered from 1 to 16, and below these numbers, the number of victims transported to each hospital. For instance, the second row indicates that a disaster is located in the Orlando International Airport and the number of victims to transport to the hospitals is 50. Then, it shows that victims are allocated in four hospitals: 8 victims to Florida Hospital East Orlando, 12 victims to Winter Park Memorial Hospital, 10 victims to Arnold Palmer Hospital for Children, and 20 victims to Dr. P. Phillips Hospital.

Table 28: Sample of Pseudo-Optimal Hospital Networks

	Hospital Networks (Hub-hospital and hub-disaster location)	**Size**	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Airport**	50	8	12	10	20												
2	**Amway Center**	50	17	12	10	11												
3	**Animal Kingdom**	50		5	10	20										15		
4	**Central Florida Regional Hospital**	50			3		22		14			4	7					
5	**Dr. P. Phillips Hospital**	50			10	20					7				13			
6	**Epcot**	50		12	10	20				7						1		
7	**Florida Citrus Bowl Stadium**	50		12	10	20										8		

Florida Hospital East Orlando: 1
Winter Park Memorial Hospital: 2
Arnold Palmer Hospital for Children: 3
Dr. P. Phillips Hospital: 4
Central Florida Regional Hospital: 5
Winnie Palmer Hospital for Women & Babies: 6
South Seminole Hospital: 7
St. Cloud Regional Medical Center: 8
Orlando Regional Medical Center: 9
Florida Hospital Orlando: 10
Florida Hospital for Children [2]: 11
Florida Hospital Apopka: 12
Florida Hospital Celebration Health: 13
Health Central: 14
South Lake hospital: 15
Florida Hospital Waterman: 16

CHAPTER SIX: DEA ANALYSIS

This chapter uses the data generated in Chapter 5 to formulate DEA models for each disaster size (small, medium, and large), seeking to identify efficient hospital networks for each hub. In this chapter, each pseudo-optimal network represents one Decision Making Units (DMU) for every DEA model computed in Chapter 6. For DEA-1, the input variables for each DMU are the following: (i) the number of beds available in the network, (ii) the number of hospitals in the network, and (iii) the average number of services offered by hospitals in the network. The output variable, for the same DEA, is the number of victims allocated in less than 40 miles from the disaster site. For DEA-2, the input variables for each DMU are (i) the number of beds available in the network, (ii) the number of hospitals in the network, and (iii) the services offered by hospitals in the network. The output variables, for DEA-2, are the followings: (i) the number of victims allocated in less than 40 miles from the disaster site, and (ii) the total ED waiting time of the hospitals in the network. Finally, this chapter includes two major sections: the data considered for each DEA model, and the DEA models and results, which outcomes are the data needed to run a regression model in Chapter 7, predicting the efficiency of hospital network in a mass casualty disaster.

6.1 Considered Data

The pseudo-optimal networks are the selected DMUs to analyze in this chapter. Table 29 shows a summary of the DMUs for the DEA calculation.

Table 29: Scenarios for the DMUs

Disaster Size	**DMUs**	**Minimum distance among hospitals**	**Minimum distance between disaster location and hospital**	**Total**
Small	Hospital network for small size disaster	13 scenarios	12 scenarios	**25**
Medium	Hospital network for medium size disaster	13 scenarios	12 scenarios	**25**
Large	Hospital network for large size disaster	13 scenarios	12 scenarios	**25**
Total		**39**	**36**	**75**

The DEA-1 analysis considers three input variables and one output variable. The input variables for each DMU are the following: (1) the number of beds available in the network, (2) the number of hospitals in the network, and (3) the average of services offered by hospitals in the network. The output variable is the number of victims allocated in less than 40 miles from the disaster site.

In addition, DEA operates more powerfully when the number of DMUs exceeds the number of the combined total of inputs and outputs at least twice (Drake and Howcroft, 1994). Following the Drake and Howcroft (1994) condition, the minimum number of DMU's needed to have a strong DEA is eight. Thus, this work uses 25 DMUs for each size of the disaster defined (small, medium, and large), as in Table 29 displays, accomplishing the condition expressed by Drake and Howcroft (1994). Table 30, Table 31, and Table 32 display the data of input variables and output variables for small, medium, and large DMUs respectively.

The DEA-2 also accomplishes the Drake and Howcroft (1994) condition. The values of the input variables and output variables are available in Appendix D. We compute a second DEA model because the first model does not include the output called "ED Waiting Time Indicator", which represents the waiting time spent by all of the victims in the hospitals within the network. The output of the hospital network for mass casualty seeks to reduce the travel distance to allocate a victim as well as reduce the time spent by victims waiting for care.

Table 30: Input and Output Variables in Small-Disaster Networks for DEA 1

	DMU Name – Disaster Size	Input Variables			Output Variable
		#Hospitals	Av_Serv.	Beds	#victims_allocated_less_40
1	Airport - Small	4	0.82	64	50
2	Amway Center - Small	4	0.82	64	50
3	Animal Kingdom - Small	4	0.84	62	50
4	Central Florida Regional Hospital - Small	5	0.80	91	0
5	Dr. P. Phillips Hospital - Small	4	0.82	75	50
6	Epcot - Small	5	0.80	69	50
7	Florida Citrus Bowl Stadium - Small	4	0.82	62	50
8	Florida Hospital Apopka - Small	6	0.84	91	21
9	Florida Hospital Celebration - Small	4	0.80	55	50
10	Florida Hospital East Orlando - Small	4	0.82	71	50
11	Florida Hospital Orlando - Small	4	0.94	67	50
12	Florida Hospital Waterman - Small	6	0.76	74	0
13	Florida Mall - Small	5	0.80	71	50
14	Health Central - Small	5	0.92	77	50
15	Hollywood Studios - Small	5	0.80	69	50
16	Magic Kingdom - Small	4	0.84	62	50
17	Mall At Millennia - Small	4	0.82	62	50
18	Orange County Convention Center - Small	4	0.82	62	50
19	Orlando Regional Medical Center - Small	3	0.90	75	50
20	SeaWorld - Small	3	0.86	57	30
21	South Lake Hospital - Small	5	0.76	67	14
22	South Seminole Hospital - Small	4	0.88	69	14
23	St Cloud Regional Medical Center - Small	4	0.80	55	7
24	Universal - Small	4	0.82	62	50
25	Winter Park Memorial Hospital - Small	4	0.90	67	50

Table 31: Input and Output Variables in Medium Size Disasters Networks for DEA 1

	DMU Name – Disaster Size	Input Variables			Output Variable
		#Hospitals	Av_Serv.	Beds	#victims_allocated_less_40
1	Airport - Medium	11	0.80	157	150
2	Amway Center - Medium	11	0.80	157	137
3	Animal Kingdom - Medium	12	0.79	158	134
4	Central Florida Regional Hospital - Medium	11	0.85	182	0
5	Dr. P. Phillips Hospital - Medium	9	0.86	156	150
6	Epcot - Medium	12	0.78	170	142
7	Florida Citrus Bowl Stadium - Medium	11	0.80	157	150
8	Florida Hospital Apopka - Medium	10	0.85	160	21
9	Florida Hospital Celebration - Medium	10	0.86	163	130
10	Florida Hospital East Orlando - Medium	9	0.86	159	130
11	Florida Hospital Orlando - Medium	10	0.86	174	150
12	Florida Hospital Waterman - Medium	11	0.83	174	0
13	Florida Mall - Medium	11	0.80	157	150
14	Health Central - Medium	10	0.87	164	150
15	Hollywood Studios - Medium	12	0.78	170	142
16	Magic Kingdom - Medium	12	0.77	164	142
17	Mall At Millennia - Medium	11	0.81	157	150
18	Orange County Convention Center - Medium	11	0.80	157	128
19	Orlando Regional Medical Center - Medium	9	0.87	160	150
20	SeaWorld - Medium	10	0.94	144	108
21	South Lake Hospital - Medium	10	0.86	168	14
22	South Seminole Hospital - Medium	10	0.87	168	14
23	St Cloud Regional Medical Center - Medium	10	0.86	163	7
24	Universal - Medium	11	0.80	157	150
25	Winter Park Memorial Hospital - Medium	10	0.87	166	150

Table 32: Input and Output Variables in Large-Disasters Networks for DEA 1

	DMU Name – Disaster Size	Input Variables			Output Variables
		#Hospitals	Av_Serv.	Beds	#victims_allocated_less_40
1	Airport - Large	16	0.82	253	234
2	Amway Center - Large	16	0.82	253	220
3	Animal Kingdom - Large	16	0.82	253	212
4	Central Florida Regional Hospital - Large	16	0.82	253	0
5	Dr. P. Phillips Hospital - Large	16	0.82	253	201
6	Epcot - Large	16	0.82	253	212
7	Florida Citrus Bowl Stadium - Large	16	0.82	253	250
8	Florida Hospital Apopka - Large	16	0.82	253	21
9	Florida Hospital Celebration - Large	16	0.82	253	136
10	Florida Hospital East Orlando - Large	16	0.82	253	139
11	Florida Hospital Orlando - Large	16	0.82	253	216
12	Florida Hospital Waterman - Large	16	0.82	253	0
13	Florida Mall - Large	16	0.82	253	234
14	Health Central - Large	16	0.82	253	181
15	Hollywood Studios - Large	16	0.82	253	212
16	Magic Kingdom - Large	16	0.82	253	212
17	Mall At Millennia - Large	16	0.82	253	227
18	Orange County Convention Center - Large	16	0.82	253	212
19	Orlando Regional Medical Center - Large	16	0.82	253	194
20	SeaWorld - Large	16	0.82	253	191
21	South Lake Hospital - Large	16	0.82	253	14
22	South Seminole Hospital - Large	16	0.82	253	14
23	St Cloud Regional Medical Center - Large	16	0.82	253	7
24	Universal - Large	16	0.82	253	234
25	Winter Park Memorial Hospital - Large	16	0.82	253	181

6.2 DEA Model and Results

The DEA-1 and DEA-2 used the CCR model[39] to calculate efficiency. The CCR model assumes constant returns to scale relationship among inputs and outputs and is useful if an increment in the unit's inputs leads to a proportional increase in its outputs. The software used to compute the DEA in this section was Frontier Analyst®[40].Table 33 and Table 34 summarize the results obtained for every disaster size in DEA-1 and DEA-2 respectively. The analysis conducted allowed the identification of the most efficient pseudo-optimal network among the set studied. The most efficient DMU (pseudo-optimal network) among the different sizes of the disasters are thirteen DMU, which present more than 90 percent efficiency on average for the three sizes of disaster. We point out that there are more efficient networks when a disaster-location is the main node, such as Airport, Amway Center, Animal Kingdom, Epcot, Florida Citrus Bowl Stadium, Florida Mall, Hollywood Studios, Magic Kingdom, Mall at Millennia, and Universal. On the other hand, we only have three networks that present a hub- hospital as the main node, such as Dr. P. Phillips Hospital, Florida Hospital Orlando, and Orlando Regional Medical Center. The main reason for this difference is that the hub-hospital networks are computed including an average distance to all the potential disaster locations.

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[39] For more details review section 3.2 Data Envelopment Analysis in this work.
[40] Frontier Analyst® software is available at http://www.banxia.com/frontier/ (accessed on August 3, 2012)

Table 33: Summary Results for DEA-1

	Network Name	Small	Medium	Large	Average Efficiency
1	Airport	98.36	100.00	93.60	97.32*
2	Amway Center	98.36	91.33	88.00	92.56*
3	Animal Kingdom	96.77	90.46	84.80	90.68*
4	Central Florida Regional Hospital	0	0	0	0.00
5	Dr. P. Phillips Hospital	98.36	100.00	80.40	92.92*
6	Epcot	100.00	97.09	84.80	93.96*
7	Florida Citrus Bowl Stadium	98.36	100.00	100.00	99.45*
8	Florida Hospital Apopka	40.00	13.76	8.40	20.72
9	Florida Hospital Celebration	100.00	84.43	54.40	79.61
10	Florida Hospital East Orlando	98.36	86.67	55.60	80.21
11	Florida Hospital Orlando	91.84	97.41	86.40	91.88*
12	Florida Hospital Waterman	0	0	0	0.00
13	Florida Mall	100.00	100.00	93.60	97.87*
14	Health Central	86.96	96.58	72.40	85.31
15	Hollywood Studios	100.00	97.09	84.80	93.96*
16	Magic Kingdom	96.77	98.35	84.80	93.31*
17	Mall At Millennia	98.36	99.9	90.80	96.35*
18	Orange County Convention Center	98.36	85.33	84.80	89.50
19	Orlando Regional Medical Center	100.00	100.00	77.60	92.53*
20	SeaWorld	69.23	78.00	76.40	74.54
21	South Lake Hospital	29.47	9.09	5.60	14.72
22	South Seminole Hospital	26.25	9.01	5.60	13.62
23	St Cloud Regional Medical Center	14.00	4.55	2.80	7.12
24	Universal	98.36	100.00	93.60	97.32*
25	Winter Park Memorial Hospital	92.31	96.58	72.40	87.10

* DMUs with higher average efficiency rate (larger than 90%)

Table 34: Summary Results for DEA-2

	DMU	Small	Medium	Large	Average Efficiency
1	Airport	99.89	100	99.58	99.82*
2	Amway Center	99.56	95.33	99.55	98.15*
3	Animal Kingdom	98.72	91.42	100	96.71*
4	Central Florida Regional Hospital	81.62	50.35	98.23	76.73
5	Dr. P. Phillips Hospital	98.15	100	98.07	98.74*
6	Epcot	100	96.55	99.84	98.80*
7	Florida Citrus Bowl Stadium	100	100	100	100.00*
8	Florida Hospital Apopka	56.56	44.78	98.23	66.52
9	Florida Hospital Celebration	100	84.42	98.07	94.16*
10	Florida Hospital East Orlando	97.94	90.16	98.07	95.39*
11	Florida Hospital Orlando	91.84	97.5	98.07	95.80*
12	Florida Hospital Waterman	81.56	47.1	98.23	75.63
13	Florida Mall	100	100	99.58	99.86*
14	Health Central	86.33	96.12	98.07	93.51*
15	Hollywood Studios	100	96.55	99.84	98.80*
16	Magic Kingdom	98.72	97.65	100	98.79*
17	Mall At Millennia	100	99.93	99.55	99.83*
18	Orange County Convention Center	100	92.09	100	97.36*
19	Orlando Regional Medical Center	100	100	98.07	99.36*
20	SeaWorld	100	100	100	100.00*
21	South Lake Hospital	86.67	47.86	98.07	77.53
22	South Seminole Hospital	37.43	45.83	98.23	60.50
23	St Cloud Regional Medical Center	65.81	42.3	98.07	68.73
24	Universal	100	100	100	100.00*
25	Winter Park Memorial Hospital	92.77	96.85	98.07	95.90*

* DMUs with higher average efficiency rate (larger than 90%)

CHAPTER SEVEN: INDEX PREDICTION AND COMPARISON

This chapter incorporates the data generated in Chapter 5 and Chapter 6 in regression models to predict the hospital efficiency. The regressions calculated in this chapter seek to facilitate the estimation of the efficiency through the mathematical relationships between the efficiency and hospital network characteristics. To study the mathematical relationships, we generated 5 hospital networks groups using cluster analysis in Minitab®. Then, we computed an ordinal logistic regression using Stata®. The results of this preliminary application are in Appendix D. However, the ordinal logistic regression analysis is not a suitable alternative based on the available data because ordinal logistic regression needs more than 75 observations to estimates the probability of belonging to outcome category k, considering 5 different categories (Agresti, 2002, pp.240-245). In addition, the interpretation of the results, given in odds, complicates the right application of an index. Since the ordinal logistic regression analysis is not a suitable alternative for the data in this research, we resorted to multiple regression analysis.

The independent variables, taken from Chapter 5, are all the characteristic of the pseudo-optimal networks, and the dependent variable, taken from Chapter 6, is the efficiency index associated to each of those networks generated using DEA. Once the regression models are calculated using DEA -1 and DEA-2, we compare these regression models with a test set previously selected from the complete data set. This chapter includes two main sections: the regression model and the comparison, which provide a linear regression equation to predict the efficiency of hospital networks in mass casualty disaster.

7.1 Regression Model based on DEA-1

This section presents a multiple regression analysis to predict the efficiency of a hospital network, as determined by the first DEA model, as a function of multiple independent variables that describe key features of the hospital network. The total list of hospital networks generated has 75 networks. We randomly selected three small-, three medium-, and three large-disaster networks from the list in order to use as a test set to validate and compare the regression models. Thus, we are researching whether the regression model can predict the efficiency generated by the DEA-1 model. Then, we defined the independent variables in this analysis, which are the following: the number of hospitals, the average distances between the disaster site and the hospitals, the number of services offered by the hospitals in the network, the number of beds, the average ED waiting time. The size of the disaster (small, medium, large) is modeled as a dummy variable. We left out the 9 networks selected as the test set and performed the analysis with the remaining 66 hospital networks of different sizes, using Minitab version 16[41].

First, we performed a "Best Subsets Regression" to get an initial assessment of the important variables in models of different size (from 1 to six variables). Figure 9 shows that the R^2 of 14 out of 15 models present a value larger than 80%. In addition, if we select only one independent variable, the "Average Distance" is the best alternative because a regression with this variable reaches an R-Square = 82.4, very high value if we compare to the other single variable model that reaches an R-Square = 3.3.

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[41] Minitab academic version can be obtained from http://www.minitab.com/en-US/academic/ (accessed on September, 2)

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Best Subsets Regression: Efficiency versus Hospitals, Avge. Distance, ...

Response is Efficiency

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                                          v v   a
                                          . .   i
                                        H       t
                                        o D S   i S
                                        s i e B n e
                                        p s r E g r S S
                                        i t v D   v i i
                                        t a i S T i z z
                                        a n c   i c e e
                       Mallows          l c e E m e _ _
Vars  R-Sq  R-Sq(adj)       Cp       S  s e s D e s 1 2
   1  82.4       82.1       3.9  15.783    X
   1   3.3        1.8     299.4  36.963          X
   2  83.6       83.0       1.5  15.366    X           X
   2  83.2       82.6       2.9  15.542    X             X
   3  83.8       83.0       2.5  15.370  X X             X
   3  83.7       83.0       2.8  15.401    X         X   X
   4  84.1       83.1       3.4  15.348  X X         X   X
   4  84.1       83.0       3.5  15.368  X X         X X
   5  84.5       83.3       3.8  15.266  X X       X X   X
   5  84.4       83.1       4.2  15.322  X X       X X X
   6  84.8       83.2       5.0  15.290  X X     X X X X
   6  84.7       83.2       5.1  15.302  X X     X X X   X
   7  84.8       82.9       7.0  15.421  X X     X X X X X
   7  84.8       82.9       7.0  15.421  X X X X X X X
   8  84.8       82.6       9.0  15.556  X X X X X X X X
```

Figure 9: Minitab Output for the Best Subsets Regression

Figure 10 displays the Stepwise analysis done to the data, and the multiple regression computed with the information from the Stepwise. This figure indicates that "average distance" and "size 1" (low-size disaster) present a low p-value, smaller than $\alpha=0.05$, indicating the model's prediction cannot be attributed to chance. Thus, "average distance" and "size 1" are significant to estimate the efficiency on the hospitals networks in the Orlando Area. The coefficient of determination R^2 indicates that 83.6 percent of the variation in the response is explained by the variables included in regression equation (7.1). This regression analysis indicated that for the variable "size 1" (i.e. 50 victims) the efficiency decrease by 8.76 points, and for the variable "Average Distance" the efficiency decrease in 1.96 points, for each mile increased in an weighed (patients or victims) distance between the disaster location and the hospitals.

In addition, this regression presents a Durbin-Watson statistic =1.82, indicating that there are not high level of autocorrelated errors. This statistic indicates that estimates of the regression coefficients are efficient, the forecasts based on the regression equations are not sub-optimal, and no significant second order effects are missing.

$$\text{Efficiency} = 134 - 1.96\ \text{Avge. Distance} - 8.76\ \text{Size\_1} \qquad (7.1)$$

Where:

Avge. Distance = the average distance between the hospitals and the disaster location

Size_1 = 1, if the disaster size is small, and 0, in other case

Size_2= 1, if the disaster size is medium, and 0, in other case

Size_3 = Size_1 =Size_2=0

Stepwise Regression: Efficiency versus Hospitals, Avge. Distance, ...

Alpha-to-Enter: 0.15 Alpha-to-Remove: 0.15

Response is Efficiency on 8 predictors, with N = 66

Step	1	2
Constant	129.8	134.4
Avge. Distance	-1.91	-1.96
T-Value	-17.30	-17.79
P-Value	0.000	0.000
Size_1		-8.8
T-Value		-2.13
P-Value		0.037
S	15.8	15.4
R-Sq	82.38	83.55
R-Sq(adj)	82.10	83.03
Mallows Cp	3.9	1.5

Regression Analysis: Efficiency versus Avge. Distance, Size_1

The regression equation is
Efficiency = 134 - 1.96 Avge. Distance - 8.76 Size_1

Predictor	Coef	SE Coef	T	P
Constant	134.362	4.401	30.53	0.000
Avge. Distance	-1.9601	0.1102	-17.79	0.000
Size_1	-8.755	4.119	-2.13	0.037

S = 15.3661 R-Sq = 83.6% R-Sq(adj) = 83.0%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	75580	37790	160.05	0.000
Residual Error	63	14875	236		
Total	65	90456			

Source	DF	Seq SS
Avge. Distance	1	74513
Size_1	1	1067

Unusual Observations

Obs	Avge. Distance	Efficiency	Fit	SE Fit	Residual	St Resid
6	43.4	13.76	49.37	2.54	-35.61	-2.35R
13	42.0	9.01	52.08	2.48	-43.07	-2.84R
29	48.1	8.40	39.98	2.80	-31.58	-2.09R
37	68.3	0.00	-8.31	5.74	8.31	0.58 X
46	48.6	5.60	39.00	2.83	-33.40	-2.21R
63	86.3	0.00	-34.79	6.22	34.79	2.48RX

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 1.82321

Figure 10: Minitab Output for the First Regression

Figure 11 shows the residual plots, which indicates the outliers in the standardized residual graph. The standardized residuals seem to have a normal distribution according the graph standardized residual, and in Figure 10, there are six unusual observations. The homoscedasticity assumption of regression is also met (standardized residuals between -3 and +3).

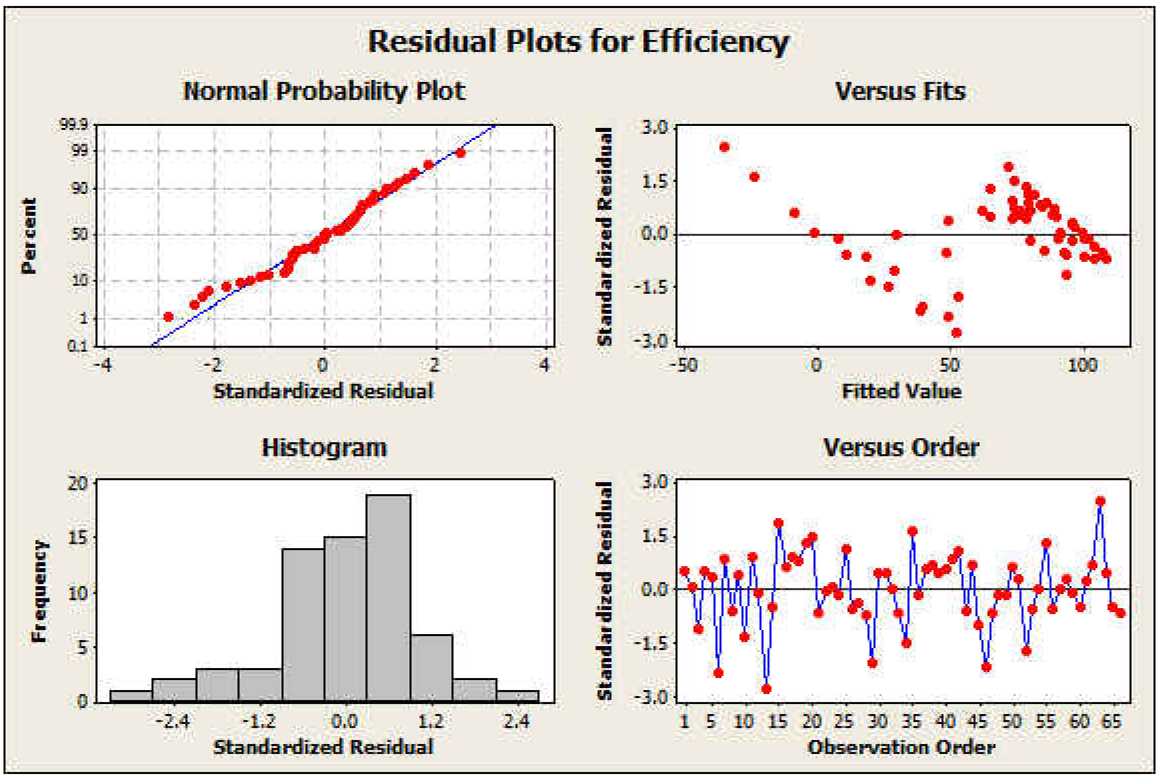

Figure 11: Minitab Output for Residual Plots for Efficiency Eq. (7.6)

Then, we performed a second multiple regression analysis for efficiency that only considers the variable "Average Distance". In this case, the efficiency decreases 1.91 points for each mile increase in the average distance between the disaster location and hospitals (weighed by patients or victims transported).

The average distance presents a p-value smaller than α=0.05. Thus, it is possible to conclude that the average distance between the hospitals and the disaster location affects the efficiency of the network. The coefficient of determination R^2 indicates that 82.4 percent of the variation in the response is explained by the regression equation (7.2). As a final point, the Durbin-Watson is 1.93, indicating that there are not high level of autocorrelated errors. This regression analysis and the residual plots are presented in Appendix E.

$$\text{Efficiency} = 130 - 1.91 \text{ Avge Distance} \qquad (7.2)$$

Where:

Avge Distance = the average distance between the hospitals and the disaster location

The analysis of the efficiency in hospital networks for DEA-1 indicates that the average distance predict the hospital network efficiency.

7.2 Regression Model based on DEA-2

This section presents a multiple regression analysis to predict the efficiency of a hospital network, as determined by the second DEA model, as a function of multiple independent variables that describe key features of the hospital network. We use efficiency data generated by DEA-2 as the dependent variable. As before, the total list of hospital networks generated has 75 networks and we use the same three small-, three medium-, and three large-disaster networks as our test set. The independent variables in this analysis are the number of hospitals, the number of children's hospitals, the number of adult's hospitals, the average distances between the disaster site and the hospitals, the number of services offered by hospitals in the network, the number of beds, and the average ED waiting time. Again, the size of the disaster is modeled as a dummy variable and, after excluding the 9 networks in our test set, we performed the analysis with the remaining 66 hospital networks of different sizes, using Minitab version 16[42]. In this section, the analysis performed is similar to the analysis made in section 7.1. However, the following variables were only included in this analysis: the number of children's hospitals, the number of adult's hospitals, and the average of services include the total number of services in the network, avoiding use the ratio used before.

First, we performed a "*Best Subset s Regression*" to select a model. The Best Subsets analysis included the variables "*Size1*" and "*Size2*" Then, we computed a Stepwise analysis, and the results were the following equations:

$$\text{Efficiency} = 135 - 15.2\ \text{Size 1} - 17.9\ \text{Size 2} - 0.490\ \text{Avg. Distance} - 0.654\ \text{Avge. Waiting Time} \tag{7.3}$$

$$\text{Efficiency} = 113 - 0.593\ \text{Avge. Waiting Time} - 0.501\ \text{Avge. Distance} - 10.8\ \text{Size 2} + 1.26\ \text{Hospitals} \tag{7.4}$$

$$\text{Efficiency} = 118 - 0.499\ \text{Avge. Distance} - 0.649\ \text{Avge. Waiting Time} + 16.6\ \text{Size 3} \tag{7.5}$$

Equation (7.3) indicates that if the disaster is size 1, the efficiency decreases by 15.2 points. If the disaster is size 2, the efficiency decreases in 17.9 points. If the "*Avge. Distance*" increases by one mile, the reduction of the efficiency is 0.49, and the efficiency decreases in 0.65 points if the Average Waiting Time increases by one minute in the hospitals of the networks.

Equation (7.4) combines the following variables: "Avge. Waiting Time", "Avge. Distance", Size 2, and the number of hospitals to predict efficiency. If the disaster is Size 2, or

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[42] Minitab academic version can be obtained from http://www.minitab.com/en-US/academic/ (accessed on September, 2)

there is an increment in the variables Avge. Waiting time, and Avge. Distance, the efficiency decreases 10.8, 0.59, and 0.50 points, respectively. On the other hand, if the number of the hospitals increases in one unit, the efficiency increases by 1.26 points. This last relationship is singular because of the homogeneity within the hospitals in the Orlando area. This homogeneity is the result of the variable selected to define services in hospitals, which only request to consider six types of services, but this variable did not differentiate the quality of the services offered for the different hospitals.

Equation (7.5) indicates that if the disaster is size 3, the efficiency increases by 16.6 points. Similarly, if the *Avge. Distance* increases by one mile the reduction of the efficiency is 0.5, and the efficiency decreases in 0.65 points if the *Avge. Waiting Time* increases by one minute in the hospitals of the networks. The value of R^2 for the three best regression equations to predict DEA-2 only explains 52% of the error. If more variables are included in the regressions, it is not possible to improve this result. However, these regressions can predict the efficiency with a Mean Average Percentage Error (MAPE) equal to 10%.

7.3 Index Predictor Comparison

7.3.1 Index Predictor Comparison DEA-1

We used a nine-network test set, previously separated from the complete data set, to compute the DEA-1 efficiency derived by multiple regressions as calculated in section 7.1. This data set was selected using the random function available in Microsoft Excel®. Table 35 displays the data corresponding to these nine networks.

Table 35: Test Data Set

	Network - size	Avge. Distance	Avge. Services	Avge. Waiting Time	Size 1	Size 2	Size 3	DEA-1 Efficiency
5	Dr. P. Phillips Hospital - small	17.72	0.82	31.78	1			98.36
15	Hollywood Studios - small	19.54	0.8	16.58	1			100.00
20	SeaWorld - small	12.82	0.86	16	1			69.23
4	Airport - Medium	15.04	0.8	17.89		1		100.00
5	Central Florida Regional Hospital - Medium	63.07	0.85	28.14		1		Not included (value=0)
7	Florida Citrus Bowl Stadium - Medium	14.28	0.8	17.89		1		100.00
10	Florida Hospital East Orlando - Large	37.44	0.82	29.96			1	55.60
15	Hollywood Studios - Large	28.11	0.82	29.32			1	84.80
24	Universal - Large	17.75	0.82	29.27			1	93.60

In order to compare these two multiple regression equations, we selected the Mean Absolute Percentage of Error (MAPE) [43] to estimate the difference between the predicted value of the efficiency and the value of the efficiency calculated using DEA in Chapter 6.

Table 36 displays the MAPE for Eq. (7.1) and Eq.(7.2).

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[43] $\mathrm{M} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|,$

Table 36: Multiple Regression Characteristics and Predictions Results

Size	**DEA-1 Efficiency**	**Eq. (7.1)**	**Eq.(7.2)**
Dr. P. Phillips Hospital - small	98.36	90.51	95.27
SeaWorld - small	69.23	100.11	104.87
Hollywood Studios - small	100.00	86.94	91.70
Airport - Medium	100.00	104.52	100.52
Central Florida Regional Hospital - Medium		10.38	6.38
Florida Citrus Bowl Stadium - Medium	100.00	106.01	102.01
Universal - Large	93.60	99.21	95.21
Hollywood Studios - Large	84.80	78.90	74.90
Florida Hospital East Orlando - Large	55.60	60.62	56.62
MAPE		12.38	10.13

In conclusion, the second multiple regression (7.2) presents better prediction features than the first equation (7.1) for efficiency computed by DEA-1. Thus, the average distance is a predictor of the hospital network efficiency.

7.3.2 Index Predictor Comparison DEA-2

We used a different nine-network test set to compare the DEA-2 efficiency regression models derived by multiple regressions as described in section 7.2. Table 37 displays the data corresponding to these nine networks.

Table 37: Test Data Sets

Size	Child_ Hosp	Adult_ Hosp	Hospitals	Services	Beds	AVGE. Waiting Time	AVGE. Distance	DEA-2 Efficiency
Orange County Convention Center - Small	3	8	4.00	20.00	62	17.84	11.02	100
Magic Kingdom - Small	3	9	4	20	62	19.8	18.81	98.72
Universal - Small	1	3	4	20	62	17.84	8.93	100
Central Florida Regional Hospital - medium	2	3	11	56	182	28.14	63.07	50.35
Florida Hospital Orlando - Medium	2	2	10	51	174	35.23	22.51	97.5
Orlando Regional Medical Center - Medium	3	6	9	47	160	34.76	19.22	100
Florida Hospital Apopka - Large	3	7	16	79	253	29.80	48.15	98.23
San Cloud Regional Medical Center - Large	3	13	16	79	253	29.84	62.82	98.07
Dr. Phillips Hospital - Large	1	3	16	79	253	29.84	30.95	98.07

In order to compare the two multiple regression models to predict DEA-2 efficiency, we selected the Mean Absolute Percentage of Error (MAPE) [44] to estimate the difference between the predicted value of the efficiency and the estimated value of the efficiency calculated in Chapter 6. Table 38 displays the MAPE for Eq. (7.3), Eq.(7.4), and Eq. (7.5).

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44 $M = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|,$

Table 38: Multiple Regression Characteristics and Model Results

Size	DEA-2 Efficiency	Eq.(7.3)	Eq.(7.4)	Eq.(7.5)
Orange County Convention Center - Small	100.00	102.73	101.94	100.92
Magic Kingdom - Small	98.72	97.63	96.87	95.76
Universal - Small	100.00	103.76	102.99	101.97
Central Florida Regional Hospital - medium	50.35	67.79	67.77	68.27
Florida Hospital Orlando - Medium	97.50	83.03	82.63	83.91
Orlando Regional Medical Center - Medium	100.00	84.95	83.3	85.85
Florida Hospital Apopka - Large	98.23	91.92	91.37	91.24
San Cloud Regional Medical Center - Large	98.07	84.7	83.99	83.88
Dr. Phillips Hospital - Large	98.07	100.32	99.96	99.79
MAPE		**10.56**	**10.78**	**10.33**

All of the equations present similar value of MAPE statistic. Thus, the "*size*" of the disaster, the number of "*hospitals*", the "*Avge. Distance*", "*Avge.Waiting Time*" are predictors of hospital network efficiency.

CHAPTER EIGHT: SUMMARY AND FUTURE RESEARCH WORK

This Chapter is divided in three subsections, summary, conclusions, and future research. The summary section discusses the main aspects of the previous chapters, giving a brief overview of this research. The conclusions part highlights the main results and applications of the methodology proposed. Finally, the last section of this chapter, the future research, recommend potential topics for further study, according the subjects developed in the previous chapters.

8.1 Summary

Disaster events have emphasized the importance of healthcare response activities due to the large number of victims in the last decades. For instance, Hurricane Katrina in New Orleans, in 2005, and the terrorist attacks in New York City and Washington, D.C., on September 11, 2001, left thousands of wounded people. In those disasters, although hospitals had disaster plans established for more than a decade, their plans were not efficient enough to handle the chaos produced by the hurricane and terrorist attacks. Moreover, government agencies and private-sector efforts have been insufficient to improve the hospital response to a catastrophic event (Auf Der Heide, 2006; Auf Der Heide, 1996; Farmer and Carlton, 2006; Schultz, Koening, and Noji, 1996).

Since hospital emergency plans were not efficient enough to handle the chaos produced by hurricanes and terrorist attacks, the JCAHO suggests collaborative planning among hospitals that provide services to a contiguous geographic area during mass casualty disasters. However, the JCAHO does not specify a methodology to determine which hospitals should be included into these cooperative plans. Thus, the problem of selecting hospitals to include in exercises and drills at the county level is a common topic in the current preparedness stages.

This study proposed an efficiency index to determine the efficient response of cooperative-networks among hospitals before an occurrence of mass casualty disaster. The index created in this research combines operation research and statistical analysis through the application of three different techniques: network optimization, data envelopment analysis (DEA), and regression analysis. The proposed methodology, in order to improve the overall hospital response to mass casualty disaster, sought the incorporation of aspects such as improving surge capacity in hospitals, reducing the liability of institutions regarding to patients' transfer, increasing the services offered in networks, and formalizing JCAHCO's conditions for conducting drills or exercises.

The Orlando area was the selected city for applying the proposed methodology because DeLia and Wood (2008) claim that the East Coast has a small surge capacity for disaster due to the rapid population growth, so this research can have more impact on this area. The definition of the size of the disasters considered the capacities of the emergency departments of the children and adults hospitals located in the Orlando area. There are 19 hospitals in the Orlando area, 15 adults hospitals and 4 children hospitals. Two adults hospitals do not have ED, and one children hospital was not open at the time of this study (Nemours Children's Clinic Hospital will open its doors on October, 2012). Then, considering the 16 remaining hospitals, the ED beds capacity is 553 beds. Taking into account the report of GAO (2009), which indicates that 47% of visits to an ED can wait for health assistance more than one hour, a revised estimate of availability ED beds was obtained. Thus, we estimated that the ED bed capacity is 260 beds in the Orlando Area.

Subsequently, the three selected disaster sizes are the followings: small size considers 50 victims, medium size considers 150 victims, and a large size considers 250 victims. These sizes represent 0.02%, 0.06%, and 0.1% of the population in Orlando City in 2011 respectively, according the U.S. Census Bureau. In addition, the number of children considered is 20 % of the disaster size, which corresponds to the distribution of the population younger than 14 years in the Orlando city, according to the same source.

In order to analyze the performance of the hospitals in a mass casualty disaster, we designed networks considering two cases, hub-hospital and hub-disaster networks. In the first case, each hospital is a hub, and the remaining hospitals are spokes. For this situation, the disaster is on an imaginary point that corresponds to the average distance from the selected hub-hospital to all the twelve potential disaster locations. In this condition, we consider thirteen hospitals as hub-hospital in the network optimizations because three hospitals present the same location that three of the thirteen remaining hospitals. This first case sought to make the reverse triage, discussed by Kelen *et al*. (2009), easier through the identification of the closest hospitals with high number of services and low waiting time to transfer patients, which allow the hub-hospitals to improve their surge capabilities. As a result, the hub-hospitals know the partners with whom they can make agreements for transferring patients, such as non-urgent and semi-urgent patients, which can wait for health care assistance for more than one hour, according to the acuity classification presented by the Emergency Nurses Association.

In the second case, after the selection of a disaster location as a hub, the hospitals are added to the network until they reach their capacities and all the victims are transported to a hospital. As a result, there are 36 optimal hospital networks, one network for each one of the twelve disaster locations, and one for each one of the three disaster sizes. This attempted to:

reduce the travel distance of the survivors because the first hour is critical to save the life of highly injured victims.

In both optimization network models, the objective function pursued to reduce the travel distance and the ED waiting time in hospitals, increase the number of services provided by a network of hospitals, and offer specialized assistance to children. In this research, children are different from adults, following the American Academy of Pediatrics report (2006), which indicates that children can be more affected by man-made disasters due to their anatomic, physiologic, immunologic, and psychological differences from adults. For that reason, the objective function is penalized, when children are not assisted at children's hospitals. The services variable follows the Janosikova (2009) criterion for measuring quality of the networks. This criterion includes the following services: surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics. In order to determine the services available in the network, we searched for all these services offered in hospitals, and then, the average of these services is calculated.

The hospital network optimization allowed the analysis of networks according to different objectives of optimization, generating information regarding to: travel distance, ED beds capacities, ED waiting time, number of survivors transported within 40 miles range, and services offered in hospitals within networks. These analyses of hospital networks allowed the generation of data, such as distribution of the victims among hospitals in mass casualty disasters, which is not available in the literature. The nonexistence of data is due to the primary health personnel's responsibility is the assistance of victims, and no reporting data. The network optimization problem used AIMMS® software for its implementation, which is detailed in Appendix C. The total number of hospital networks generated is 75.

The DEA analyzed these 75 networks (i.e. DMU's) to estimate their comparative efficiency. We implemented the DEA in Frontier Analyst Pro®. To define inputs and outputs variables, we analyzed the objective of a hospital network in a disaster, which is save lives, assisting survivors promptly. The DEA-1 model included as an output variable of the DMU's the number of survivors allocated in less than a 40 miles range. The input variables included for each DMU are the followings:

i. The number of beds available in the network, as Ferrier and Valdmanis (2004) proposed to measure efficiency

ii. The number of hospitals available in the network

iii. The average of services offered by hospitals in the network, as Janosikova (2009) suggested for reducing hospital network size

As a result, the DEA-1 classified 37 high efficient networks (i.e. efficiency range 100-90), 18 efficient networks (i.e. efficiency range 89-70), and 20 non-efficient networks (i.e. efficiency range 69-0). This analysis allows the assignment of an efficiency value for each pseudo-hospital network identified in the optimization analysis.

Similarly, the DEA-2 classified 61 high efficient networks (i.e. efficiency range 100-90), 5 efficient networks (i.e. efficiency range 89-70), and 9 non-efficient networks (i.e. efficiency range 69-0). In this analysis, we included an indicator of the ED waiting time as an output variable. This analysis allows the assignment of an efficiency value for each pseudo-hospital network identified in the optimization analysis.

To study the relationship between efficiency and the network's characteristics, we generated 5 groups using cluster analysis in Minitab®, and later, we computed an ordinal logistic regression in Stata®. However, ordinal logistic regression needs more than 75 observations to estimates the probability of belonging to outcome category k or a lower category compared to belonging to category high than k. Other problem is the interpretation of the results given as odds, which complicate the right application of an index. The results of this preliminary application are detailed in Appendix D.

Since the ordinal logistic regression analysis was not a suitable alternative for the data in this research, we reverted to multiple regression analysis. For each DEA model, we randomly selected three small-, three medium-, and three large-disaster networks from the list in order to use these nine networks as a test set, which we used to compare the performance of several alternative regression models.

Then, we determined multiple regression models using Minitab Software® to determine the index. This regression analysis proved that the size of the disaster, the number of hospitals, the "*Average Distance*", and "*Average Waiting Time*" are predictors of hospital network efficiency. The models generated a MAPE around 10%. Thus, the regressions developed to facilitate the estimation of the efficiency index in predefined hospital networks are suitable predictors of the efficiency as generated by the DEA models.

Finally, the efficiency index (calculated by DEA or estimated by regression), should allow hospital managers to assess which hospitals should be associated in a cooperative network in order to transfer survivors for different disaster location-size scenarios. In addition, institutions such as JCAHO can use this index to evaluate the cooperatives hospitals' plans requested in JCAHO's new Environment of Care Standard. Furthermore, the index should facilitate the decision making to emergency managers in the following aspects:

i. Comparing hospital networks alternatives in order to select the network that best cover a defined population

ii. Evaluating the impact on the efficiency when a new hospital is added into a hospital network.

iii. Defining cooperation policies within an established number of hospitals to participate in the drills required by JCAHO.

iv. Identifying partners with whom hospitals should sign agreement for transferring patients in case of disasters, avoiding future liabilities problems.

In conclusion, the hypothesis was validated, so network optimization, DEA, and regressions analysis can be combined to create an index of efficiency to measure the performance of predefined-hospital networks in a mass casualty disaster. Although we applied the methodology to a specific county, this methodology can be applied in other cities or countries, in the world.

8.2 Conclusions

This research demonstrated that is feasible to create an Index to measure efficiency in predefined networks by combining network optimization, data envelopment analysis, and statistical analysis. The proposed methodology offers a framework to evaluate efficiency in predefined hospital networks for emergency managers and health institutions. Similarly, this methodology can support the JCAHO's interest in promoting cooperative emergency plans among hospitals that provide services to a contiguous geographic area.

The two cases used in network design (hub-hospital and Hub-disaster's location) helped to identify the most relevant hospitals that should have cooperative agreements in case of occurrence of a mass casualty disaster. In the Orlando area, the list of hospitals with a high frequency in the pseudo-optimal networks' list included the following hospitals: Arnold Palmer Hospital for Children, Dr. P. Phillips Hospital, Florida Hospital East Orlando, Winter Park Memorial Hospital, Central Florida Regional Hospital, Orlando Regional Medical Center, Florida Hospital Orlando, Florida Hospital for Children, South Seminole Hospital, Winnie Palmer Hospital, and St. Cloud Regional Medical Center. This list included all the children's hospitals in the Orlando area because this research followed the suggestions made by the American Academy of Pediatrics report (2006). In addition, the network optimization process proved being a high-quality source of data, suitable for DEA application.

This research proved that the size of the disaster, the number of hospitals, the "*Average. Distance*", and "*Average Waiting Time*" are predictors of hospital network efficiency. The models generated had a MAPE around 10%. Thus, the preferred index developed (Efficiency = 118 - 0.499 Avge. Distance - 0.649 Avge. Waiting Time + 16.6 Size 3) to facilitate the estimation of the efficiency in predefined hospital networks is a suitable predictor of the efficiency.

The application of the proposed methodology determined the efficient response of cooperative-networks among hospitals before an occurrence of mass casualty disaster in the Orlando area. In conclusion, we validated the hypothesis, so network optimization, DEA, and statistics analysis can be combined to create an index of efficiency to measure the performance of predefined-hospital networks in a mass casualty disaster. Although we applied the methodology to a specific county, this methodology could be applied in other cities or countries.

The regressions proposed to predict the efficiency estimated by DEA can be applied only in a city or area that has the same characteristic than the Orlando area, which are the following:

i. Networks must have a rate of services lager than 0.76. This index is calculated as the following:

   a) Six services are identified in each hospital; these services are surgery, orthopedics or traumatology, internal medicine or cardiology, neurology, gynecology and obstetrics, and pediatrics.

   b) The total services found in each hospital are divided by six

   c) All of the rates are averaged to obtain the rate of the services in the network.

ii. The number of survivors is less than 47% of the bed capacity Emergency Department in the area studied.

iii. All hospitals in the network have Emergency Department.

iv. All hospitals are located in less than 48 miles from the disaster sites.

v. None of the Emergency Departments has more than 60 minutes of waiting time.

Furthermore, the proposed methodology has a high impact on the policies to establish guidelines to coordinate drills and exercises, improving hospital response. This methodology does not allow a free association among hospitals because this methodology integrates different ownership hospitals into a hospital network, if this increases the efficiency of the hospital network. The proposed methodology, in special the efficiency index, can support the operational objectives of the 2012 ESF#8 for Florida, such as "... Maintain and implement the Florida Public Health and Healthcare Preparedness Strategic Plan to manage risk and build response capabilities [and] ... Conduct and participate in trainings and exercises to validate, test and improve plans and procedures" (The State of Florida Final Draft Comprehensive Emergency Management Plan 2012, ESF # 8 Appendix-, pp.1- 20). This methodology supports the Joint Commission Officers in the creation of more specific guidelines to certificate hospitals based on their Emergency plans and annual exercises.

8.3 Future Research

The potential future work would expand and improve this methodology to create an index to estimate the efficiency of predefined hospital networks ability to respond to a mass casualty disaster, includes the following aspects:

i. Data:

   a. This research only used public information available though hospitals websites, so this research can be improved by using more information regarding to existing resources in hospitals, such as number of physicians, nurses, general health personnel, and hospital's characteristic, such as daily surge capacity.

   b. The definition of the hospital's services can be improved by using indicators of quality or size of the services. For instance, the services can be classified according the number and quality of resources available at the hospital. In this research, the criterion proposed by Janosikova (2009) does not allow to discriminate between large hospital departments and small hospital departments.

ii. Hospital Network Optimization:

   a. The objective function can be improved by using any scalarization technique and weighted vectors to assign relevance to the different objectives. Janosikova's work (2009) is a potential example to review in this area.

b. It is possible to use different weighted vectors in the objective function to study the dependence between the weight assigned and the hospital networks obtained. This can help to balance the public objectives and the private objectives within hospital networks.

iii. Frontier Analysis:

a. The Data Envelopment Analysis can be improved defining more outputs for the DMU's (i.e. Hospital Networks), such as some measures of time spent in the network before receiving care, or the percent of patients that need to be transferred.

b. If a network includes hospitals that belong to different owners, coordination can be difficult. The inclusion of any function that connects the number of hospitals' owners, and the ability to coordinate actions in a suitable period, can improve the analysis of efficiency.

- The study of the behavior of the project teams can guide to create a relationship among efficiency and size of the group of people in the project. Chernoguz (2010) research is a clear example of how the size of the team increases the entropy, which influences the completion of the projects.
- The use of Social Network Analysis can support the identification of the important relationships among ownership of the hospitals into a network, and the impact of those relationships on the hospital network performance.
-

iv. Regression Analysis

a. The regression analysis can be improved incorporating more hospital networks into the analysis. This action can allow the use of other techniques that requires a bigger data set, such as ordered logistic regressions.

APPENDIX A: HOSPITAL - HOSPITAL DISTANCES

Table A.1: Minimum Distance between Hospitals (miles)

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19
H1	0	0	13.5	8.2	4.2	4.7	4.7	4.7	4.7	13.7	3.5	11.2	24.5	11.3	28.4	23.7	19.3	34.4	29.7
H2	0	0	13.5	8.2	4.2	4.7	4.7	4.7	4.7	13.7	3.5	11.2	24.5	11.3	28.4	23.7	19.3	34.4	29.7
H3	13	13	0	22.4	15.7	16.4	16.4	16.4	16.4	25.5	15.8	12.9	37.9	12.2	24.3	35.4	23.7	19.4	37.9
H4	8.2	8.2	21.1	0	7.7	7.3	7.3	7.3	7.3	17.3	6.7	15.3	15.3	21.1	35.7	32.1	24.7	47.5	31.4
H5	4.3	4.3	16.3	7.8	0	8	8	8	8	18	7.5	9.4	23.5	15.5	33.3	28.5	18.6	36	34.5
H6	4.4	4.4	15.4	6.9	7.6	0	0	0	0	10.5	0.7	16.1	15.7	11.1	25.7	20.5	26.7	35.7	23.9
H7	4.4	4.4	15.4	6.9	7.6	0	0	0	0	10.5	0.7	16.1	15.7	11.1	25.7	20.5	26.7	35.7	23.9
H8	4.4	4.4	15.4	6.9	7.6	0	0	0	0	10.5	0.7	16.1	15.7	11.1	25.7	20.5	26.7	35.7	23.9
H9	4.4	4.4	15.4	6.9	7.6	0	0	0	0	10.5	0.7	16.1	15.7	11.1	25.7	20.5	26.7	35.7	23.9
H10	13.9	13.9	21.1	17.4	17.6	10.7	10.7	10.7	10.7	0	11	25.2	17.1	12	26.7	10.2	35.4	42	22.8
H11	3.3	3.3	14.8	6.3	7.5	0.7	0.7	0.7	0.7	10.9	0	14.8	16.1	10.6	25.2	20.9	25.4	34.7	24.1
H12	11.3	11.3	11.8	15.3	10.4	14.9	14.9	14.9	14.9	23.9	14.3	0	29.9	22.5	37.9	34.1	10.3	30.4	41
H13	23.9	23.9	37.2	15.1	23.5	15.6	15.6	15.6	15.6	17	16	29.7	0	27.7	39.1	18.6	35.2	54.3	14.4
H14	11.3	11.3	12.2	21.1	15.5	11.1	11.1	11.1	11.1	12	10.6	22.5	0	0	15.5	23.5	32.4	28.3	29.4
H15	28.4	28.4	24.3	35.7	33.3	25.7	25.7	25.7	25.7	26.7	25.2	37.9	0	15.3	0	26.8	49	22.9	41.5
H16	23.7	23.7	35.4	32.1	28.5	20.5	20.5	20.5	20.5	10.2	20.9	34.1	0	24.3	26.7	0	44.3	48.5	18.3
H17	19.3	19.3	23.7	24.7	18.6	26.7	26.7	26.7	26.7	35.4	25.4	10.3	0	32.7	48.5	44.1	0	29.2	49.3
H18	34.4	34.4	19.4	47.5	36	35.7	35.7	35.7	35.7	42	34.7	30.4	0	28.1	22.3	52.4	29.3	0	56.7
H19	29.7	29.7	37.9	31.4	34.5	23.9	23.9	23.9	23.9	22.8	24.1	41	14.4	30.2	41.6	18.3	47.4	56.8	0

Table A.2: Maximum Time between Hospital (minutes)

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19
H1	0	0	28	18	13	13	13	13	13	24	12	23	34	23	41	29	32	55	37
H2	0	0	28	18	13	13	13	13	13	24	12	23	34	23	41	29	32	55	37
H3	26	26	0	35	32	31	31	31	31	38	30	29	52	23	43	48	39	37	56
H4	17	17	38	0	18	13	13	13	13	29	15	31	22	32	57	41	28	67	46
H5	14	14	31	18	0	22	22	22	22	28	21	21	34	30	50	37	33	58	51
H6	14	14	32	15	20	0	0	0	0	16	5	29	32	21	48	34	39	56	34
H7	14	14	32	15	20	0	0	0	0	16	5	29	32	21	48	34	39	56	34
H8	14	14	32	15	20	0	0	0	0	16	5	29	32	21	48	34	39	56	34
H9	14	14	32	15	20	0	0	0	0	16	5	29	32	21	48	34	39	56	34
H10	29	29	44	33	36	25	25	25	25	0	20	49	27	24	46	19	50	68	34
H11	13	13	30	14	19	3	3	3	3	22	0	28	33	20	48	34	38	56	34
H12	21	21	24	32	22	27	27	27	27	35	26	0	45	33	53	45	21	53	49
H13	32	32	50	21	33	31	31	31	31	28	31	44	0	37	54	31	52	75	30
H14	23	23	23	32	30	21	21	21	21	24	20	33	37	0	28	33	43	49	43
H15	41	41	43	57	50	48	48	48	48	46	48	53	54	30	0	49	63	45	65
H16	29	29	48	41	37	34	34	34	34	19	34	45	31	31	46	0	55	67	35
H17	32	32	39	28	33	39	39	39	39	50	38	21	52	44	63	53	0	46	62
H18	55	55	37	67	58	56	56	56	56	68	56	53	75	44	44	68	57	0	88
H19	37	37	56	46	51	34	34	34	34	34	34	49	30	44	63	34	61	74	0

Table A.3:Minimum Time between Hospital (minutes)

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19
H1	0	0	25	16	10	12	12	12	12	20	10	21	32	20	40	29	29	50	37
H2	0	0	25	16	10	12	12	12	12	20	10	21	32	20	40	29	29	50	37
H3	24	24	0	33	30	29	29	29	29	34	28	27	49	21	35	44	36	30	49
H4	15	15	34	0	17	13	13	13	13	22	12	30	20	28	47	37	28	64	44
H5	11	11	28	17	0	20	20	20	20	28	19	20	32	28	49	37	28	53	45
H6	12	12	31	12	19	0	0	0	0	16	4	27	29	19	38	26	33	56	34
H7	12	12	31	12	19	0	0	0	0	16	4	27	29	19	38	26	33	56	34
H8	12	12	31	12	19	0	0	0	0	16	4	27	29	19	38	26	33	56	34
H9	12	12	31	12	19	0	0	0	0	16	4	27	29	19	38	26	33	56	34
H10	24	24	35	25	31	20	20	20	20	0	20	39	27	21	38	15	46	56	33
H11	11	11	30	11	18	3	3	3	3	16	0	26	27	18	37	25	32	55	33
H12	18	18	24	26	21	22	22	22	22	30	21	0	42	32	52	41	17	52	49
H13	30	30	48	20	32	27	27	27	27	27	26	41	0	34	51	23	36	64	28
H14	20	20	21	28	28	19	19	19	19	21	18	32	0	0	25	31	39	42	36
H15	40	40	35	47	49	38	38	38	38	38	37	52	0	22	0	40	59	36	52
H16	29	29	44	37	37	26	26	26	26	15	25	41	0	29	37	0	55	62	30
H17	29	29	36	28	28	33	33	33	33	46	32	17	0	42	62	51	0	44	59
H18	50	50	30	64	53	56	56	56	56	56	55	52	0	37	35	59	44	0	65
H19	37	37	49	44	45	34	34	34	34	33	33	49	28	35	52	33	58	70	0

Table A.4: Number of Routes between Hospitals

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19
H1	0	0	3	3	3	3	3	3	3	2	3	3	2	3	2	1	2	2	1
H2	0	0	3	3	3	3	3	3	3	2	3	3	2	3	2	1	2	2	1
H3	3	3	0	3	3	3	3	3	3	3	3	3	3	3	3	3	2	3	3
H4	3	3	3	0	3	1	1	1	1	2	2	3	2	3	3	3	1	3	3
H5	3	3	3	3	0	3	3	3	3	2	3	3	2	3	2	1	3	2	2
H6	3	3	3	3	3	0	0	0	0	1	3	3	3	3	3	3	3	3	2
H7	3	3	3	3	3	0	0	0	0	1	3	3	3	3	3	3	3	3	2
H8	3	3	3	3	3	0	0	0	0	1	3	3	3	3	3	3	3	3	2
H9	3	3	3	3	3	0	0	0	0	1	3	3	3	3	3	3	3	3	2
H10	2	2	3	3	3	2	2	2	2	0	1	3	2	2	3	2	3	3	2
H11	3	3	3	3	3	1	1	1	1	2	0	3	3	3	3	3	3	3	2
H12	2	2	3	3	2	2	2	2	2	2	3	0	3	3	2	2	3	3	1
H13	2	2	3	2	3	3	3	3	3	2	3	3	0	3	3	2	2	3	3
H14	3	3	3	3	3	3	3	3	3	2	3	3	3	0	2	3	3	3	3
H15	2	2	3	3	2	3	3	3	3	3	3	2	3	2	0	3	3	2	3
H16	1	1	3	3	1	3	3	3	3	2	2	2	2	2	3	0	3	3	3
H17	2	2	2	1	3	3	3	3	3	3	3	3	2	3	3	3	0	2	3
H18	2	2	3	3	2	3	3	3	3	2	3	3	3	3	3	3	3	0	3
H19	1	1	3	3	2	2	2	2	2	2	2	1	3	3	3	2	3	2	0

APPENDIX B: HOSPITAL - DISASTER LOCATION DISTANCES

Table B.1: Minimum Time between Hospitals and Potential Disaster Location

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
H1	9	28	41	34	34	12	19	42	16	23	24	18
H2	9	28	41	34	34	12	19	42	16	23	24	18
H3	27	40	38	41	44	27	35	41	31	34	35	29
H4	12	19	42	35	35	12	20	43	17	25	26	20
H5	16	29	48	40	41	19	26	49	23	30	31	25
H6	16	20	38	30	30	9	16	38	12	20	21	15
H7	16	20	38	30	30	9	16	38	12	20	21	15
H8	16	20	38	30	30	9	16	38	12	20	21	15
H9	16	20	38	30	30	9	16	38	12	20	21	15
H10	16	22	26	17	17	17	16	26	12	8	7	8
H11	5	20	37	30	30	8	15	38	12	36	20	14
H12	23	40	56	47	48	26	33	56	30	37	38	32
H13	28	18	35	26	27	29	12.7	35	31	23	23	28
H14	18	27	26	28	31	14	20	29	17	20	22	15
H15	37	44	43	38	41	33	38	44	34	37	38	32
H16	25	27	21	14	15	26	24	21	22	16	17	18
H17	32	37	63	56	56	33	41	64	38	45	45	41
H18	52	62	60	62	66	51	56	63	52	55	45	50
H19	33	31	44	35	35	34	24	43	52	28	45	28

Table B.2: Maximum Time between hospitals and potential disaster location

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
H1	11	29	45	34	34	14	25	48	20	28	26	22
H2	11	29	45	34	34	14	25	48	20	28	26	22
H3	30	47	45	47	52	29	38	48	34	43	43	36
H4	14	20	45	40	41	15	26	48	21	29	29	24
H5	17	30	51	44	44	20	30	51	25	33	34	27
H6	17	25	41	35	35	9	17	41	13	20	23	15
H7	17	25	41	35	35	9	17	41	13	20	23	15
H8	17	25	41	35	35	9	17	41	13	20	23	15
H9	17	25	41	35	35	9	17	41	13	20	23	15
H10	16	24	28	21	24	19	19	29	17	10	7	9
H11	7	24	40	36	30	8	17	43	14	40	20	14
H12	24	42	58	57	57	29	36	59	32	40	48	40
H13	32	19	40	35	35	36	12.7	44	33	27	26	30
H14	19	36	30	31	32	15	26	33	19	26	24	20
H15	37	54	44	48	50	38	48	47	44	48	49	43
H16	25	31	24	17	19	26	27	24	25	22	20	18
H17	37	48	65	57	57	39	45	65	44	46	47	47
H18	55	72	69	66	66	56	63	69	60	67	47	59
H19	33	36	48	39	39	34	27	47	60	35	47	39

Table B.3: Minimum Distance between Hospitals and Potential Disaster Locations (miles)

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
H1	3.1	13.8	25.8	23.1	23.2	4.2	10.4	26.9	8.8	14.1	15.4	11.3
H2	3.1	13.8	25.8	23.1	23.2	4.2	10.4	26.9	8.8	14.1	15.4	11.3
H3	13.7	27	22.5	31.2	32.8	13.3	20.2	24.1	18.7	21.2	25.7	17.5
H4	7.8	9.5	27.8	26.5	26.6	7.8	13.8	29.6	12.2	17.5	18.7	14.7
H5	6.6	13.7	29.4	26.7	26.8	7.8	14	30.4	12.4	17.7	19.2	14.9
H6	6.6	10.7	23.7	19.7	19.9	2.7	7.5	24.7	5.5	10.7	12.8	8
H7	6.6	10.7	23.7	19.7	19.9	2.7	7.5	24.7	5.5	10.7	12.8	8
H8	6.6	10.7	23.7	19.7	19.9	2.7	7.5	24.7	5.5	10.7	12.8	8
H9	6.6	10.7	23.7	19.7	19.9	2.7	7.5	24.7	5.5	10.7	12.8	8
H10	11	15	12.1	9	9.3	10.1	7.2	14.5	6.6	3.8	2.6	3.6
H11	1.1	11.1	22.4	20	20.2	2.1	7.4	23.5	5.8	24.2	13	8.3
H12	13.4	20.1	37	33.4	33.6	14.2	20.7	37.3	19.1	24.4	26.4	21.6
H13	21.1	8.6	24.8	19.4	19.6	20.9	15.1	24.7	19	16.4	16.2	19.2
H14	10.2	22.4	13	21.3	23.6	8.9	16.3	14	12.9	12.6	17.4	9.9
H15	25.7	35.2	21.6	27.1	29.1	23.5	28.5	22.7	24.3	26.7	28.8	24
H16	21	21.9	10.8	6.8	7.6	20.7	16	10.7	16.5	11.6	10	13.6
H17	24.4	31.2	49.8	44.4	44.6	25.6	31.7	49.6	28.4	35.4	37.4	30.9
H18	33.5	50.4	39.2	47.5	49.8	33.1	40	40.3	39.5	42	37.4	38.5
H19	24.1	17.7	26.3	20.9	21.1	23.8	17.2	26.1	39.5	20.2	37.4	22.3

Table B.4: Number of Alternatives Routes

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
H1	3	3	3	1	1	3	3	3	2	3	2	2
H2	3	3	3	1	1	3	3	3	2	3	2	2
H3	3	3	3	3	3	3	3	3	3	3	3	3
H4	2	3	3	3	3	2	3	3	2	3	3	3
H5	3	2	3	2	2	3	3	2	3	3	3	2
H6	3	2	3	2	3	3	3	2	2	1	3	1
H7	3	2	3	2	3	3	3	2	2	1	3	1
H8	3	2	3	2	3	3	3	2	2	1	3	1
H9	3	2	3	2	3	3	3	2	2	1	3	1
H10	1	3	3	3	3	2	3	3	2	3	1	3
H11	3	3	3	2	1	3	2	3	2	3	1	1
H12	3	3	3	3	3	3	3	3	3	3	3	3
H13	2	3	3	3	3	3	2	3	3	3	2	3
H14	3	3	3	2	2	2	3	3	2	2	2	3
H15	2	3	3	3	3	2	3	3	3	3	3	2
H16	1	3	3	3	3	1	3	3	2	2	2	1
H17	3	3	3	3	3	2	3	3	3	3	3	3
H18	3	3	3	3	3	3	3	3	3	3	3	3
H19	1	3	3	3	3	2	2	3	3	2	3	3

APPENDIX C: NETWORK OPTIMIZATION

C.1. AIMMS PROGRAM FOR HUB-HOSPITAL

```
MAIN MODEL Main_HospitalNetwork

  DECLARATION SECTION

    MATHEMATICAL PROGRAM:
       identifier   :  LeastValueOfNetwork
       objective    :  ValueOfNetwork
       direction    :  minimize
       constraints  :  AllConstraints
       variables    :  AllVariables
       type         :  Automatic ;

    CONSTRAINT:
       identifier   :  VictimsRestrictionChildren
       index domain :  l
       definition   :  sum[i,Transport(l,i)] <=
round(PercentageOfChildren*VictimsDisater(l),0) ;

    CONSTRAINT:
       identifier   :  VictimsRestrictionAdults
       index domain :  l
       definition   :  sum [i,transport(l,i)]+ sum[j,Transport(l,j)] =
VictimsDisater(l) ;

    CONSTRAINT:
       identifier   :  CapacityRestrictionAdults
       index domain :  j
       definition   :  sum[l,Transport(l,j)]<=
FreeCapacityPercentage*CapacityHospital(j) ;

    CONSTRAINT:
       identifier   :  CapacityRestrictionChildren
       index domain :  i
       definition   :  sum[l,Transport(l,i)]<=
FreeCapacityPercentage*CapacityHospital(i) ;

    SET:
       identifier   :  AdultsHospital
       subset of    :  Hospitals
       index        :  j ;

    SET:
       identifier   :  DisaterLocations
       index        :  l ;

    SET:
       identifier   :  ChildrenHospital
       subset of    :  Hospitals
       index        :  i ;

    SET:
       identifier   :  Hospitals
       index        :  h ;

    PARAMETER:
       identifier   :  VictimsDisater
```

```
       index domain :  (l) ;

    PARAMETER:
       identifier   :  PercentageOfChildren ;

    PARAMETER:
       identifier   :  WaitingTime
       index domain :  (h) ;

    PARAMETER:
       identifier   :  WaitingTimeChildren
       index domain :  (i) ;

    PARAMETER:
       identifier   :  WaitingTimeAdults
       index domain :  (j) ;

    PARAMETER:
       identifier   :  FreeCapacityPercentage ;

    PARAMETER:
       identifier   :  CapacityHospital
       index domain :  (h) ;

    PARAMETER:
       identifier   :  DistanceLocationHospital
       index domain :  (l,h) ;

    PARAMETER:
       identifier   :  QualityHospital
       index domain :  (h) ;

    VARIABLE:
       identifier   :  Transport
       index domain :  (l,h)
       range        :  integer ;

    VARIABLE:
       identifier   :  WaitingTimeNetwork
       range        :  free
       definition   :  sum[(l,h),WaitingTime(h)*Transport(l,h)] ;

    VARIABLE:
       identifier   :  Children_Adult_Hospital
       range        :  free
       definition   :  round(PercentageOfChildren*sum[l,VictimsDisater(l)],0)-
sum[(l,i),Transport(l,i)] ;

    VARIABLE:
       identifier   :  TotalVictimsAssigned
       range        :  free
       definition   :  sum[(l,h),Transport(l,h)] ;

    VARIABLE:
       identifier   :  ValueOfNetwork
       range        :  free
       definition   :  DistanceNetwork-
QualityNetwork+sum[l,VictimsDisater(l)]*Children_Adult_Hospital+WaitingTimeNetwork/sum
[l,VictimsDisater(l)]
```

```
        comment      :  "-
30*sum[(l,h),QualityHospital(h)*transport(l,h)]++sum[(l,h),DistanceLocationHospital(l,
h)*transport(l,h)]" ;

    VARIABLE:
       identifier   :  Childrendistribution
       range        :  free
       definition   :  (sum[i,CapacityHospital(i)]- sum[(l,i),Transport(l,i)]) ;

    VARIABLE:
       identifier   :  DistanceNetwork
       range        :  free
       definition   :  sum[(l,h),DistanceLocationHospital(l,h)*transport(l,h)] ;

    VARIABLE:
       identifier   :  QualityNetwork
       range        :  free
       definition   :  sum[(l,h),QualityHospital(h)*transport(l,h)] ;

  ENDSECTION  ;

  PROCEDURE
    identifier :  MainInitialization

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  MainExecution
    body       :
      solve LeastValueOfNetwork;
      if (LeastValueOfNetwork.ProgramStatus <> 'optimal') then
      empty Transport,ValueOfNetwork;
      endif;

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  MainTermination
    body       :
      return DataManagementExit();

  ENDPROCEDURE  ;

ENDMODEL Main_HospitalNetwork ;
```

C.2. AIMMS PROGRAM FOR HUB-DISASTER LOCATION

```
MAIN MODEL Main_HospitalNetwork

  DECLARATION SECTION

    PARAMETER:
       identifier   :  WaitingTime
       index domain :  (h) ;

    PARAMETER:
       identifier   :  WaitingTimeChildren
       index domain :  (i) ;

    PARAMETER:
       identifier   :  WaitingTimeAdults
       index domain :  (j) ;

    MATHEMATICAL PROGRAM:
       identifier   :  LeastValueOfNetwork
       objective    :  ValueOfNetwork
       direction    :  minimize
       constraints  :  AllConstraints
       variables    :  AllVariables
       type         :  Automatic ;

    PARAMETER:
       identifier   :  PercentageOfChildren ;

    CONSTRAINT:
       identifier   :  VictimsRestrictionChildren
       index domain :  l
       definition   :  sum[i,Transport(l,i)] <=
round(PercentageOfChildren*VictimsDisater(l),0) ;

    CONSTRAINT:
       identifier   :  VictimsRestrictionAdults
       index domain :  l
       definition   :  sum [i,transport(l,i)]+ sum[j,Transport(l,j)] =
VictimsDisater(l) ;

    CONSTRAINT:
       identifier   :  CapacityRestrictionAdults
       index domain :  j
       definition   :  sum[l,Transport(l,j)]<=
FreeCapacityPercentage*CapacityHospital(j) ;

    CONSTRAINT:
       identifier   :  CapacityRestrictionChildren
       index domain :  i
       definition   :  sum[l,Transport(l,i)]<=
FreeCapacityPercentage*CapacityHospital(i) ;

    SET:
       identifier   :  AdultsHospital
       subset of    :  Hospitals
       index        :  j ;
```

```
    SET:
       identifier   :  DisaterLocations
       index        :  l ;

    SET:
       identifier   :  ChildrenHospital
       subset of    :  Hospitals
       index        :  i ;

    SET:
       identifier   :  Hospitals
       index        :  h ;

    PARAMETER:
       identifier   :  VictimsDisater
       index domain :  (l) ;

    PARAMETER:
       identifier   :  FreeCapacityPercentage ;

    PARAMETER:
       identifier   :  CapacityHospital
       index domain :  (h) ;

    PARAMETER:
       identifier   :  DistanceLocationHospital
       index domain :  (l,h) ;

    PARAMETER:
       identifier   :  QualityHospital
       index domain :  (h) ;

    VARIABLE:
       identifier   :  Transport
       index domain :  (l,h)
       range        :  integer ;

    VARIABLE:
       identifier   :  WaitingTimeNetwork
       range        :  free
       definition   :  sum[(l,i),WaitingTimeChildren(i)*Transport(l,i)] +
sum[(l,j),WaitingTimeAdults(j)*Transport(l,j)] ;

    VARIABLE:
       identifier   :  Children_Adult_Hospital
       range        :  free
       definition   :  round(PercentageOfChildren*sum[l,VictimsDisater(l)],0)-
sum[(l,i),Transport(l,i)] ;

    VARIABLE:
       identifier   :  TotalVictimsAssigned
       range        :  free
       definition   :  sum[(l,h),Transport(l,h)] ;

    VARIABLE:
       identifier   :  ValueOfNetwork
       range        :  free
       definition   :  sum[(l,h),DistanceLocationHospital(l,h)*transport(l,h)]-
30*sum[(l,h),QualityHospital(h)*transport(l,h)]+(sum[l,VictimsDisater(l)])*(sum[i,Capa
cityHospital(i)]- sum[(l,i),Transport(l,i)])+ waitingtimenetwork ;
```

```
    VARIABLE:
       identifier   :  DistanceNetwork
       range        :  free
       definition   :  sum[(l,h),DistanceLocationHospital(l,h)*transport(l,h)] ;

    VARIABLE:
       identifier   :  QualityNetwork
       range        :  free
       definition   :  sum[(l,h),QualityHospital(h)*transport(l,h)] ;

  ENDSECTION  ;

  PROCEDURE
    identifier :  MainInitialization

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  MainExecution
    body       :
      solve LeastValueOfNetwork;
      if (LeastValueOfNetwork.ProgramStatus <> 'optimal') then
      empty Transport,ValueOfNetwork;
      endif;

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  MainTermination
    body       :
      return DataManagementExit();

  ENDPROCEDURE  ;

ENDMODEL Main_HospitalNetwork ;
```

C.3. RESULTS

Table C.3: Optimal Networks

Hospital Networks (Hub-hospital and hub-disaster location)	Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Airport	50	8	12	10	20												
Amway Center	50	17	12	10	11												
Animal Kingdom	50		5	10	20										15		
Central Florida Regional Hospital	50			3		22		14			4	7					
Dr. P. Phillips Hospital	50			10	20					7				13			
Epcot	50		12	10	20				7						1		
Florida Citrus Bowl Stadium	50		12	10	20										8		
Florida Hospital Apopka	50			3				14			4	7	7		15		
Florida Hospital Celebration	50			10	20				7					13			
Florida Hospital East Orlando	50	17	12	10						11							
Florida Hospital Orlando	50		7	3							33	7					
Florida Hospital Waterman	50			3								7	7		3	14	16
Florida Mall	50	1	12	10	20				7								
Health Central	50			3							18	7	7		15		
Hollywood Studios	50		12	10	20				7						1		
Magic Kingdom	50		5	10	20										15		
Mall At Millennia	50		12	10	20										8		
Orange County Convention Center	50		12	10	20										8		
Orlando Regional Medical Center	50			10						27	13						
SeaWorld	50			10	20	20											
South Lake Hospital	50			3								7			15	14	11
South Seminole Hospital	50			3				14			26	7					
St Cloud Regional Medical Center	50			10	20				7					13			
Universal	50		12	10	20										8		
Winter Park Memorial Hospital	50		12	3							28	7					

Hospital Networks (Hub-hospital and hub-disaster location)	Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Airport	150	17	12	15	20	22	14	14	7			1			15	13	
Amway Center	150	17	12	15	20	22	14	14	7			1			15	13	
Animal Kingdom	150	17	12	15	20		14	12	7			1	7		15	14	16
Central Florida Regional Hospital	150	17	12	15		22	8	14		1	33	7	7			14	
Dr. P. Phillips Hospital	150		12	15	20		14			27	33	1		13	15		
Epcot	150	17	12	15	20	8	14	14	7			1		13	15	14	
Florida Citrus Bowl Stadium	150	17	12	15	20	22	14	14	7			1			15	13	
Florida Hospital Apopka	150		12	15			8	14		27	33	7	7		15		12
Florida Hospital Celebration	150		5	15	20		8		7	27	33	7		13	15		
Florida Hospital East Orlando	150	17	12	15	20		14	11		27	33	1					
Florida Hospital Orlando	150	17	12	15	2		8	14		27	33	7			15		
Florida Hospital Waterman	150		12	15			8	14		9	33	7	7		15	14	16
Florida Mall	150	17	12	15	20	22	14	14	7			1			15	13	
Health Central	150		4	15	20		8			27	33	7	7		15	14	
Hollywood Studios	150	17	12	15	20	8	14	14	7			1		13	15	14	
Magic Kingdom	150	17	12	15	20		14	14	7			1		13	15	14	8
Mall At Millennia	150	17	12	15	20	22	14	14				1	6		15	14	
Orange County Convention Center	150	17	12	15	20	22	14	14	7			1			15	13	
Orlando Regional Medical Center	150	17	12	15	20		14			27	33	1			11		
SeaWorld	150	17	12	15	20		14	4				1			15	14	16
South Lake Hospital	150			15	20		8			15	33	7	7		15	14	16
South Seminole Hospital	150	5	12	15		22	8	14		27	33	7	7				
St Cloud Regional Medical Center	150		5	15	20		14		7	27	33	1		13	15		
Universal	150	17	12	15	20	22	14	14	7			1			15	13	
Winter Park Memorial Hospital	150	17	12	15	10		8	14		27	33	7	7				

Hospital Networks (Hub-hospital and hub-disaster location)	Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Airport	250	17	12	15	20	22	14	14	7	27	33	7	7	10	15	14	16
Amway Center	250	17	12	15	20	22	14	14	7	27	33	7	7	10	15	14	16
Animal Kingdom	250	17	12	15	20	22	14	14	7	27	30	7	7	13	15	14	16
Central Florida Regional Hospital	250	17	12	15	20	22	14	14	4	27	33	7	7	13	15	14	16
Dr. P. Phillips Hospital	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13
Epcot	250	17	12	15	20	22	14	14	7	24	33	7	7	13	15	14	16
Florida Citrus Bowl Stadium	250	17	12	15	20	22	14	14	7	27	33	7	7	10	15	14	16
Florida Hospital Apopka	250	17	12	15	20	22	14	14	4	27	33	7	7	13	15	14	16
Florida Hospital Celebration	250	17	12	15	20	19	14	14	7	27	33	7	7	13	15	14	16
Florida Hospital East Orlando	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13
Florida Hospital Orlando	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13
Florida Hospital Waterman	250	17	12	15	20	22	14	14	4	27	33	7	7	13	15	14	16
Florida Mall	250	17	12	15	20	22	14	14	7	27	33	7	7	10	15	14	16
Health Central	250	17	12	15	20	19	14	14	7	27	33	7	7	13	15	14	16
Hollywood Studios	250	17	12	15	20	22	14	14	7	24	33	7	7	13	15	14	16
Magic Kingdom	250	17	12	15	20	22	14	14	7	27	30	7	7	13	15	14	16
Mall At Millennia	250	17	12	15	20	22	14	14	7	27	33	7	7	10	15	14	16
Orange County Convention Center	250	17	12	15	20	22	14	14	7	27	30	7	7	13	15	14	16
Orlando Regional Medical Center	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13
SeaWorld	250	17	12	15	20	22	14	14	7	27	30	7	7	13	15	14	16
South Lake Hospital	250	17	12	15	20	19	14	14	7	27	33	7	7	13	15	14	16
South Seminole Hospital	250	17	12	15	20	22	14	14	4	27	33	7	7	13	15	14	16
St Cloud Regional Medical Center	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13
Universal	250	17	12	15	20	22	14	14	7	27	30	7	7	13	15	14	16
Winter Park Memorial Hospital	250	17	12	15	20	22	14	14	7	27	33	7	7	13	15	14	13

Florida Hospital East Orlando	1
Winter Park Memorial Hospital	2
Arnold Palmer Hospital for Children	3
Dr. P. Phillips Hospital	4
Central Florida Regional Hospital	5
Winnie Palmer Hospital for Women & Babies	6
South Seminole Hospital	7
St. Cloud Regional Medical Center	8
Orlando Regional Medical Center	9
Florida Hospital Orlando	10
Florida Hospital for Children [2]	11
Florida Hospital Apopka	12
Florida Hospital Celebration Health	13
Health Central	14
South Lake hospital	15
Florida Hospital Waterman	16

APPENDIX D: DATA FOR DEA 2

Table D.1: Input and Output in Small Networks for DEA 2

	DMU Name	Input Variables			Output Variables	
		#Hospitals	Services *Patients	.Beds	#victims_allocated_less_40	Waiting time Indicator (1/wt)*10000
1	Airport	4.00	248	64	50	11.01
2	Amway Center	4.00	248	64	50	10.40
3	Animal Kingdom	4.00	255	62	50	10.10
4	Central Florida Regional Hospital	5.00	243	91	0.1	9.92
5	Dr. P. Phillips Hospital	4.00	247	75	50	6.29
6	Epcot	5.00	241	69	50	12.06
7	Florida Citrus Bowl Stadium	4.00	248	62	50	11.21
8	Florida Hospital Apopka	6.00	250	91	21	7.08
9	Florida Hospital Celebration	4.00	240	55	50	7.64
10	Florida Hospital East Orlando	4.00	248	71	50	7.42
11	Florida Hospital Orlando	4.00	279	67	50	4.33
12	Florida Hospital Waterman	6.00	230	74	0.1	9.39
13	Florida Mall	5.00	241	71	50	12.03
14	Health Central	5.00	278	77	50	5.00
15	Hollywood Studios	5.00	241	69	50	12.06
16	Magic Kingdom	4.00	255	62	50	10.10
17	Mall At Millennia	4.00	248	62	50	11.21
18	Orange County Convention Center	4.00	248	62	50	11.21
19	Orlando Regional Medical Center	3.00	273	75	50	4.11
20	SeaWorld	3.00	260	57	30	12.50
21	South Lake Hospital	5.00	228	67	14	9.89
22	South Seminole Hospital	4.00	265	69	14	4.84
23	St Cloud Regional Medical Center	4.00	240	55	7	7.64
24	Universal	4.00	248	62	50	11.21
25	Winter Park Memorial Hospital	4.00	269	67	50	4.84

Table D.2: Input and Output in Medium Networks for DEA 2

	DMU Name	Input Variables			Output Variables	
		#Hospitals	Services *Patients	.Beds	#victims_allocated_less_40	Waiting time Indicator (1/wt)*10000
1	Airport	11.00	719	157	150	3.73
2	Amway Center	11.00	719	157	137	3.73
3	Animal Kingdom	12.00	711	158	134	3.46
4	Central Florida Regional Hospital	11.00	765	182	0.1	2.37
5	Dr. P. Phillips Hospital	9.00	773	156	150	1.82
6	Epcot	12.00	705	170	142	3.15
7	Florida Citrus Bowl Stadium	11.00	719	157	150	3.73
8	Florida Hospital Apopka	10.00	767	160	21	1.92
9	Florida Hospital Celebration	10.00	773	163	130	1.78
10	Florida Hospital East Orlando	9.00	775	159	130	1.95
11	Florida Hospital Orlando	10.00	772	174	150	1.89
12	Florida Hospital Waterman	11.00	749	174	0.1	2.22
13	Florida Mall	11.00	719	157	150	3.73
14	Health Central	10.00	787	164	150	1.85
15	Hollywood Studios	12.00	705	170	142	3.15
16	Magic Kingdom	12.00	697	164	142	3.15
17	Mall At Millennia	11.00	731	157	150	3.52
18	Orange County Convention Center	11.00	719	157	128	3.73
19	Orlando Regional Medical Center	9.00	786	160	150	1.92
20	SeaWorld	10.00	609	144	108	4.28
21	South Lake Hospital	10.00	775	168	14	2.05
22	South Seminole Hospital	10.00	779	168	14	1.96
23	St Cloud Regional Medical Center	10.00	773	163	7	1.81
24	Universal	11.00	719	157	150	3.73
25	Winter Park Memorial Hospital	10.00	779	166	150	1.86

Table D.3: Input and Output in Large Networks for DEA 2

	DMU Name	Input Variables			Output Variables	
		#Hospitals	Services *Patients	.Beds	#victims_allocated_less_40	Waiting time Indicator (1/wt)*10000
1	Airport	16.00	1232	253	234	1.36
2	Amway Center	16.00	1232	253	220	1.36
3	Animal Kingdom	16.00	1226	253	212	1.37
4	Central Florida Regional Hospital	16.00	1232	253	0.1	1.34
5	Dr. P. Phillips Hospital	16.00	1232	253	201	1.34
6	Epcot	16.00	1229	253	212	1.36
7	Florida Citrus Bowl Stadium	16.00	1232	253	250	1.36
8	Florida Hospital Apopka	16.00	1232	253	21	1.34
9	Florida Hospital Celebration	16.00	1229	253	136	1.34
10	Florida Hospital East Orlando	16.00	1232	253	139	1.34
11	Florida Hospital Orlando	16.00	1232	253	216	1.34
12	Florida Hospital Waterman	16.00	1232	253	0.1	1.34
13	Florida Mall	16.00	1232	253	234	1.36
14	Health Central	16.00	1229	253	181	1.34
15	Hollywood Studios	16.00	1229	253	212	1.36
16	Magic Kingdom	16.00	1226	253	212	1.37
17	Mall At Millennia	16.00	1232	253	227	1.36
18	Orange County Convention Center	16.00	1226	253	212	1.37
19	Orlando Regional Medical Center	16.00	1232	253	194	1.34
20	SeaWorld	16.00	1226	253	191	1.37
21	South Lake Hospital	16.00	1229	253	14	1.34
22	South Seminole Hospital	16.00	1232	253	14	1.34
23	St Cloud Regional Medical Center	16.00	1232	253	7	1.34
24	Universal	16.00	1226	253	234	1.37
25	Winter Park Memorial Hospital	16.00	1232	253	181	1.34

APPENDIX E: DATA FOR REGRESSIONS

Table E.1: Data for Multiple Regressions

Victims	Waiting Time	Service	Hosp	Children Hospital	Adult Hospital	Service 1	Beds	AVGE. Waiting Time	AVGE. Distance	Size 1	Size 2	Size 3	Efficiency
250	7350	1232	16	3	8	79	253	29.40	17.21	0	0	1	99.55
150	3171	705	12	3	9	56	170	21.14	25.60	0	1	0	96.55
250	7461	1232	16	3	7	79	253	29.84	29.34	0	0	1	98.07
150	2888	711	12	1	3	57	158	19.25	27.43	0	1	0	91.42
50	2064	265	4	3	13	21	69	41.28	37.14	1	0	0	37.43
50	1413	250	6	2	4	30	91	28.26	39.39	1	0	0	56.56
250	7329	1229	16	1	4	79	253	29.32	28.44	0	0	1	99.84
150	2842	731	11	1	3	54	157	18.95	16.63	0	1	0	99.93
150	5221	767	10	3	13	51	160	34.81	43.36	0	1	0	44.78
150	2338	609	10	3	13	41	144	15.59	24.81	0	1	0	100.00
250	7461	1232	16	2	2	79	253	29.84	35.25	0	0	1	98.07
150	2684	719	11	3	13	53	157	17.89	21.96	0	1	0	95.33
250	7317	1226	16	3	13	78	253	29.27	29.36	0	0	1	100.00
50	1347	248	4	3	13	20	71	26.94	24.07	1	0	0	97.94
250	7317	1226	16	3	8	78	253	29.27	17.75	0	0	1	100.00
50	2064	269	4	3	13	22	67	41.28	23.68	1	0	0	92.77
150	3171	697	12	3	13	56	164	21.14	26.77	0	1	0	97.65
50	1065	230	6	3	13	28	74	21.30	68.32	1	0	0	81.56
150	4513	749	11	3	8	55	174	30.09	80.39	0	1	0	47.10
150	2684	719	11	3	13	53	157	17.89	17.81	0	1	0	100.00
150	2684	719	11	3	13	53	157	17.89	19.63	0	1	0	100.00
250	7449	1232	16	2	4	79	253	29.80	86.30	0	0	1	98.23
250	7350	1232	16	3	13	79	253	29.40	15.27	0	0	1	99.58
250	7461	1229	16	3	13	79	253	29.84	43.47	0	0	1	98.07
150	5101	779	10	3	7	52	168	34.01	41.98	0	1	0	45.83

Victims	Waiting Time	Service	Hosp	Children Hospital	Adult Hospital	Service1	Beds	AVGE. Waiting Time	AVGE. Distance	Size 1	Size 2	Size 3	Efficiency
250	7350	1232	16	1	3	79	253	29.40	22.37	0	0	1	99.55
250	7317	1226	16	3	13	78	253	29.27	20.73	0	0	1	100.00
50	1309	240	4	3	7	19	55	26.18	27.52	1	0	0	100.00
50	892	248	4	3	13	20	62	17.84	8.72	1	0	0	100.00
250	7350	1232	16	3	8	79	253	29.40	13.61	0	0	1	100.00
250	7461	1229	16	3	7	79	253	29.84	64.55	0	0	1	98.07
150	5623	773	10	1	3	52	163	37.49	35.41	0	1	0	84.42
50	831	241	5	1	4	24	71	16.62	13.12	1	0	0	100.00
250	7461	1232	16	1	2	79	253	29.84	27.60	0	0	1	98.07
250	7350	1232	16	3	8	79	253	29.40	19.36	0	0	1	99.58
250	7449	1232	16	3	13	79	253	29.80	68.94	0	0	1	98.23
50	2309	279	4	3	13	22	67	46.18	17.36	1	0	0	91.84
50	962	248	4	3	8	20	64	19.24	12.86	1	0	0	99.56
250	7461	1232	16	3	6	79	253	29.84	37.44	0	0	1	98.07
150	5371	779	10	3	7	52	166	35.81	28.07	0	1	0	96.85
250	7329	1229	16	3	13	79	253	29.32	28.11	0	0	1	99.84
50	1309	240	4	3	7	19	55	26.18	49.21	1	0	0	65.81
150	5492	773	9	3	13	46	156	36.61	22.86	0	1	0	100.00
250	7317	1226	16	1	3	78	253	29.27	30.61	0	0	1	100.00
150	5137	775	9	1	3	47	159	34.25	28.79	0	1	0	90.16
50	2432	273	3	3	13	16	75	48.64	15.26	1	0	0	100.00
250	7317	1226	16	3	7	78	253	29.27	20.71	0	0	1	100.00
150	5527	773	10	1	3	52	163	36.85	54.70	0	1	0	42.30
150	5409	787	10	3	13	52	164	36.06	30.77	0	1	0	96.12
50	2001	278	5	3	7	28	77	40.02	26.74	1	0	0	86.33

Victim	Waiting Time	Service	Hosp	Children Hospital	Adult Hospital 1	Service 1	Beds	AVGE. Waiting Time	AVGE. Distance	Size 1	Size 2	Size 3	Efficiency
50	1008	243	5	3	8	24	91	20.16	53.99	1	0	0	81.62
50	1011	228	5	3	13	23	67	20.22	48.82	1	0	0	86.67
150	2684	719	11	1	3	53	157	17.89	15.04	0	1	0	100.00
250	7449	1232	16	2	2	79	253	29.80	48.65	0	0	1	98.23
50	829	241	5	3	9	24	69	16.58	19.54	1	0	0	100.00
150	4885	775	10	2	3	52	168	32.57	58.91	0	1	0	47.86
250	7461	1229	16	2	3	79	253	29.84	36.79	0	0	1	98.07
150	2684	719	11	1	3	53	157	17.89	14.28	0	1	0	100.00
150	2684	719	11	1	3	53	157	17.89	20.93	0	1	0	92.09
50	800	260	3	1	2	16	57	16.00	12.82	1	0	0	100.00
50	908	248	4	3	8	20	64	18.16	9.05	1	0	0	99.89
150	3171	705	12	1	4	56	170	21.14	25.14	0	1	0	96.55
50	892	248	4	3	13	20	62	17.84	9.26	1	0	0	100.00
50	990	255	4	3	9	20	62	19.80	18.22	1	0	0	98.72
50	829	241	5	3	13	24	69	16.58	19.94	1	0	0	100.00
50	1589	247	4	3	6	20	75	31.78	17.72	1	0	0	98.15

Table E.2: Test Data

Victims	Services	Child_Hosp	Adult_Hosp	Hospitals	Services	Beds	Waiting Time	AVGE. Waiting Time	AVGE. Distance	Efficiency
150	765	2	3	11	56	182	4221	28.14	63.07	50.35
250	1232	3	7	16	79	253	7449	29.796	48.15	98.23
50	248	3	8	4.00	20.00	62	892	17.84	11.02	100
150	772	2	2	10	51	174	5284	35.22667	22.51	97.5
250	1232	3	13	16	79	253	7461	29.844	62.82	98.07
250	1232	1	3	16	79	253	7461	29.844	30.95	98.07
50	255	3	9	4	20	62	990	19.8	18.81	98.72
150	786	3	6	9	47	160	5214	34.76	19.22	100
50	248	1	3	4	20	62	892	17.84	8.93	100

Regression Analysis: Efficiency versus Avge. Distance

```
The regression equation is
Efficiency = 130 - 1.91 Avge. Distance


Predictor         Coef  SE Coef       T      P
Constant       129.796    3.946   32.89  0.000
Avge. Distance  -1.9072   0.1103  -17.30  0.000


S = 15.7829   R-Sq = 82.4%   R-Sq(adj) = 82.1%


Analysis of Variance

Source          DF     SS     MS       F      P
Regression       1  74513  74513  299.13  0.000
Residual Error  64  15942    249
Total           65  90456


Unusual Observations

          Avge.
Obs  Distance  Efficiency     Fit  SE Fit  Residual  St Resid
  6      43.4       13.76   47.10    2.36    -33.34     -2.14R
 13      42.0        9.01   49.73    2.28    -40.72     -2.61R
 35      80.4        0.00  -23.52    5.77     23.52      1.60 X
 46      48.6        5.60   37.01    2.74    -31.41     -2.02R
 52      37.1       26.25   58.96    2.05    -32.71     -2.09R
 63      86.3        0.00  -34.80    6.38     34.80      2.41RX

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.


Durbin-Watson statistic = 1.93105
```

Figure E.1: Minitab Output for Efficiency vs Avge.Distance, DEA-1

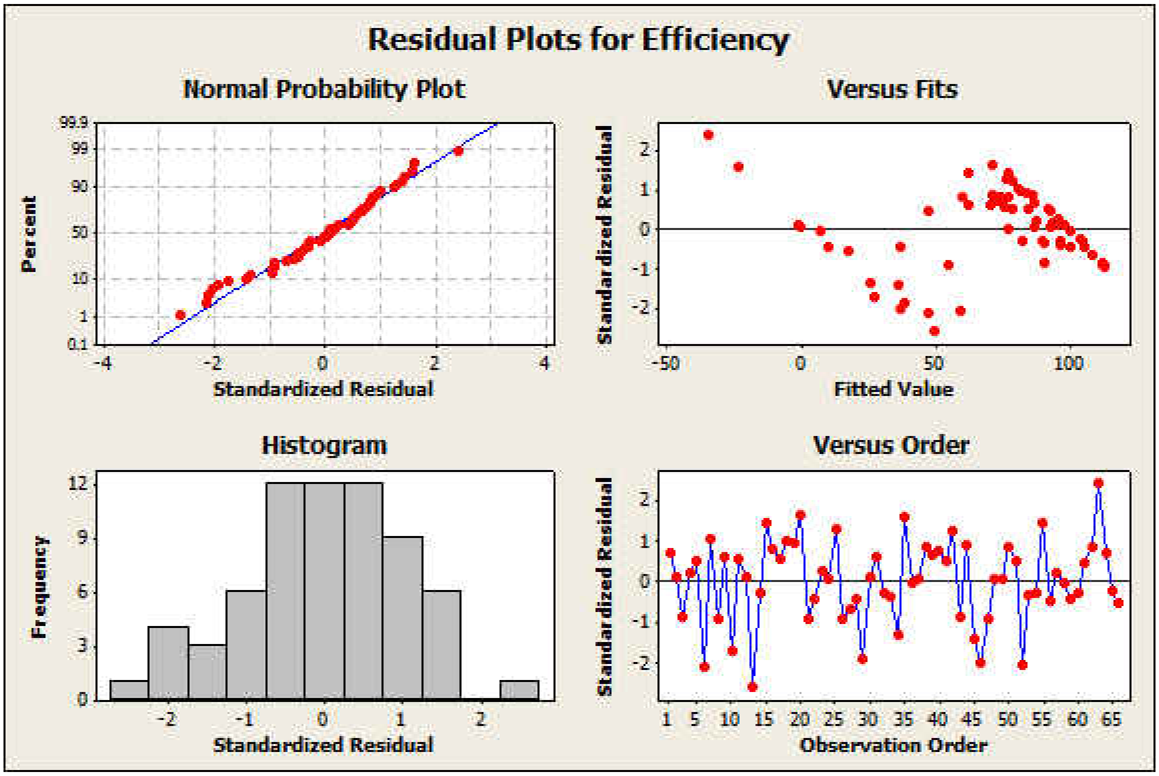

Figure E.2: Minitab Output for Residual Plots (Efficiency vs Avge.Distance) DEA-1

Results for: REGRESSION DATA.MTW

Best Subsets Regression: Efficiency versus Child_Hosp, Adult_Hosp, ...

```
Response is Efficiency

                                                A
                                                V
                                                .

                                                W A
                                                a V
                                        C A S   i .
                                        h d e   t       H
                                        i u r   i D     o
                                        l l v   n i     s
                                        d t i   g s S S p
                                        _ _ c     t i i i
                                        H H e B T a z z t
                                        o o s e i n e e a
                       Mallows          s s _ d m c     l
Vars  R-Sq  R-Sq(adj)       Cp       S  p p 1 s e e 1 2 s
   1  26.5       25.3     28.6  14.557            X
   1  10.7        9.3     48.0  16.040          X
   2  37.2       35.2     17.3  13.555            X     X
   2  36.2       34.2     18.6  13.668        X   X
   3  45.0       42.3      9.8  12.794            X X   X
   3  44.5       41.8     10.4  12.849            X   X X
   4  52.1       49.0      3.0  12.030          X X X X
   4  51.6       48.4      3.6  12.096          X X   X X
   5  53.1       49.2      3.8  12.007        X X X X X
   5  53.0       49.0      3.9  12.024      X   X X X X
   6  53.9       49.3      4.7  11.999      X   X X X X X
   6  53.6       48.9      5.1  12.041    X   X X X X X
   7  54.2       48.7      6.4  12.062      X X X X X X X
   7  54.2       48.6      6.5  12.073    X X   X X X X X
   8  54.4       48.0      8.1  12.143    X X X X X X X X
   8  54.3       47.9      8.3  12.156  X X X   X X X X X
   9  54.5       47.2     10.0  12.236  X X X X X X X X X
```

Figure E.3: Best Subsets Regression

Stepwise Regression: Efficiency versus Child_Hosp, Adult_Hosp, ...

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Efficiency on 9 predictors, with N = 66


Step                  1       2       3       4       5       6
Constant         106.41   96.34   71.05   82.94  153.46  134.91

AVGE. Distance      -0.503  -0.568  -0.570  -0.518  -0.480  -0.490
T-Value           -4.80   -5.71   -6.06   -5.60   -5.10   -5.43
P-Value           0.000   0.000   0.000   0.000   0.000   0.000

Hospitals                  1.17    2.95    2.98   -1.09
T-Value                    3.29    4.27    4.50   -0.42
P-Value                   0.002   0.000   0.000   0.675

Size 1                             20.7    20.5   -28.0   -15.2
T-Value                            2.95    3.05   -0.92   -4.09
P-Value                           0.004   0.003   0.362   0.000

AVGE. Waiting Time                          -0.50   -0.70   -0.65
T-Value                                   -2.52   -3.03   -3.29
P-Value                                   0.014   0.004   0.002

Size 2                                            -23.9   -17.9
T-Value                                           -1.63   -4.86
P-Value                                           0.108   0.000

S                  14.6    13.6    12.8    12.3    12.1    12.0
R-Sq              26.47   37.24   44.97   50.17   52.28   52.14
R-Sq(adj)         25.32   35.24   42.31   46.90   48.30   49.00
Mallows Cp         28.6    17.3     9.8     5.4     4.8     3.0
```

Figure E.4: Stepwise Regression

Regression Analysis: Efficiency versus Size 1, Size 2, ...

```
The regression equation is
Efficiency = 135 - 15.2 Size 1 - 17.9 Size 2 - 0.490 AVGE. Distance
             - 0.654 AVGE. Waiting Time


Predictor             Coef  SE Coef      T      P
Constant           134.910    6.520  20.69  0.000
Size 1             -15.229    3.725  -4.09  0.000
Size 2             -17.925    3.691  -4.86  0.000
AVGE. Distance      -0.49032  0.09030  -5.43  0.000
AVGE. Waiting Time   -0.6538   0.1985  -3.29  0.002


S = 12.0296   R-Sq = 52.1%   R-Sq(adj) = 49.0%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       4   9616.3  2404.1  16.61  0.000
Residual Error  61   8827.4   144.7
Total           65  18443.7


Source            DF  Seq SS
Size 1             1    67.5
Size 2             1  2243.4
AVGE. Distance       1  5735.3
AVGE. Waiting Time   1  1570.1


Unusual Observations

Obs  Size 1  Efficiency    Fit  SE Fit  Residual  St Resid
  5    1.00       37.43  74.48    3.90    -37.05     -3.26R
  6    1.00       56.56  81.89    2.83    -25.33     -2.17R
  9    0.00       44.78  72.97    3.16    -28.19     -2.43R
 22    0.00       98.23  73.11    5.39     25.12      2.34R
 25    0.00       45.83  74.17    3.06    -28.34     -2.44R
 48    0.00       42.30  66.07    3.71    -23.77     -2.08R

R denotes an observation with a large standardized residual.


Durbin-Watson statistic = 1.96091
```

Figure E.5: Regression Analysis

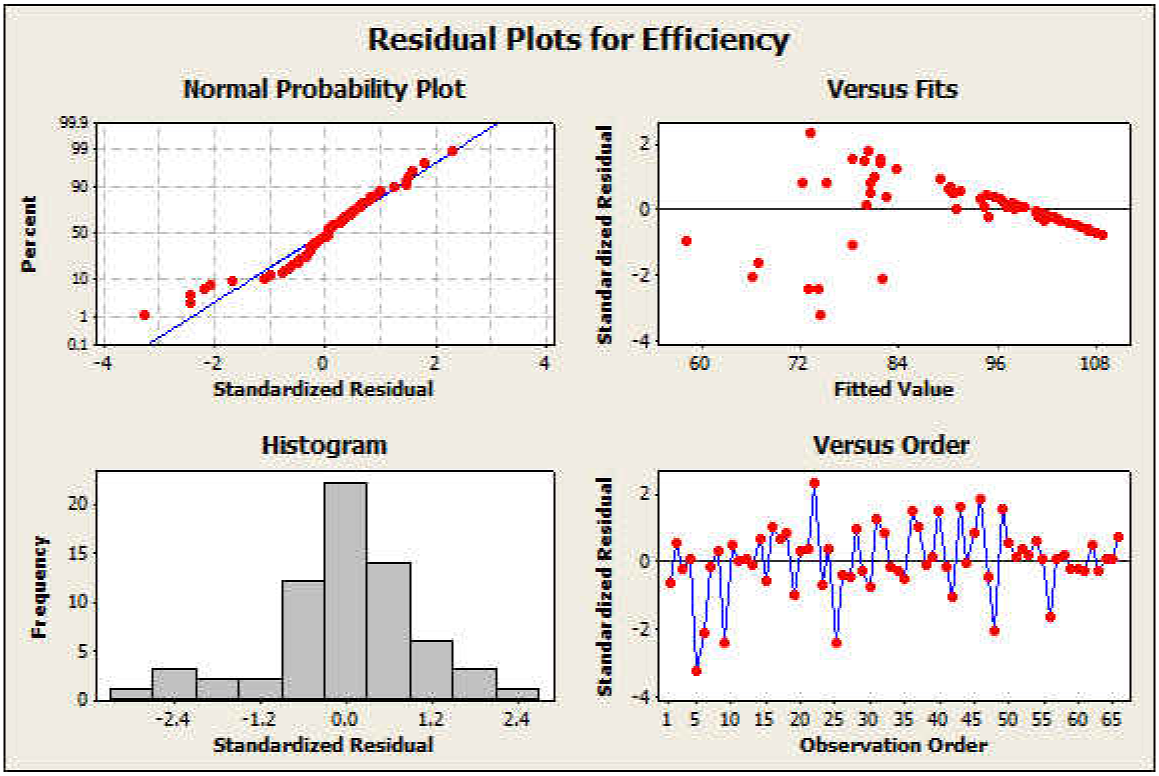

Figure E.6: Residual Plots for Efficiency

Regression Analysis: Efficiency versus AVGE. Waiting , AVGE. Distance, ...

```
The regression equation is
Efficiency = 113 - 0.593 AVGE. Waiting Time - 0.501 AVGE. Distance - 10.8 Size 2
             + 1.26 Hospitals


Predictor              Coef  SE Coef      T      P
Constant            113.042    6.284  17.99  0.000
AVGE. Waiting Time  -0.5929   0.1981  -2.99  0.004
AVGE. Distance     -0.50080  0.09127  -5.49  0.000
Size 2              -10.761    3.187  -3.38  0.001
Hospitals            1.2637   0.3173   3.98  0.000


S = 12.0960   R-Sq = 51.6%   R-Sq(adj) = 48.4%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       4   9518.6  2379.7  16.26  0.000
Residual Error  61   8925.1   146.3
Total           65  18443.7


Source            DF  Seq SS
AVGE. Waiting Time   1  1977.5
AVGE. Distance       1  3728.2
Size 2             1  1491.6
Hospitals          1  2321.4


Unusual Observations

         AVGE.
     Waiting
Obs     Time  Efficiency    Fit  SE Fit  Residual  St Resid
  5     41.3       37.43  75.02    3.87    -37.59     -3.28R
  6     28.3       56.56  84.14    2.50    -27.58     -2.33R
  9     34.8       44.78  72.57    3.20    -27.79     -2.38R
 22     29.8       98.23  72.38    5.39     25.85      2.39R
 25     34.0       45.83  73.73    3.10    -27.90     -2.39R
 48     36.8       42.30  65.68    3.75    -23.38     -2.03R

R denotes an observation with a large standardized residual.


Durbin-Watson statistic = 1.94400
```

Figure E.7: Regression Analysis

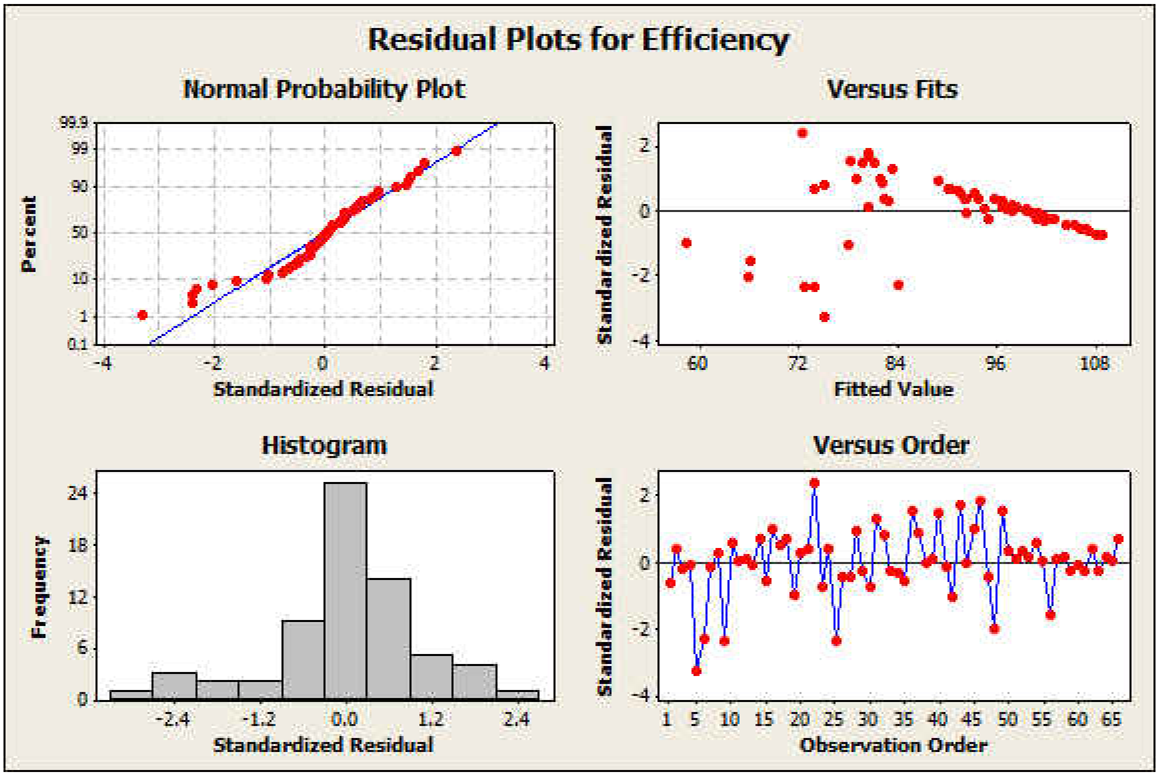

Figure E.8: Residual Plots for Efficiency

Results for: REGRESSION DATA.MTW

Best Subsets Regression: Efficiency versus Hospitals, Child_Hosp, ...

```
Response is Efficiency

                                                  A
                                                  V
                                                  .

                                                  W A
                                                  a V
                                          C A S   i .
                                        H h d e   t
                                        o i u r   i D
                                        s l l v   n i
                                        p d t i   g s S S
                                        i _ _ c     t i i
                                        t H H e B T a z z
                                        a o o s e i n e e
                       Mallows          l s s _ d m c
Vars  R-Sq  R-Sq(adj)       Cp       S  s p p 1 s e e 1 3
   1  26.5       25.3     28.6  14.557              X
   1  11.0        9.7     47.6  16.011                  X
   2  43.3       41.5      9.8  12.881              X   X
   2  37.2       35.2     17.3  13.555  X           X
   3  51.7       49.4      1.5  11.985            X X   X
   3  45.0       42.3      9.8  12.794  X           X X
   4  52.6       49.5      2.4  11.973      X     X X   X
   4  52.4       49.3      2.6  11.995        X   X X   X
   5  53.7       49.8      3.1  11.936  X     X   X X   X
   5  53.1       49.2      3.8  12.007          X X X X X
   6  53.9       49.3      4.7  11.999  X     X   X X X X
   6  53.9       49.2      4.8  12.007  X   X X   X X   X
   7  54.2       48.7      6.4  12.062  X     X X X X X X
   7  54.2       48.6      6.5  12.073  X   X X   X X X X
   8  54.4       48.0      8.1  12.143  X   X X X X X X X
   8  54.3       47.9      8.3  12.156  X X X X   X X X X
   9  54.5       47.2     10.0  12.236  X X X X X X X X X
```

Figure E.9: Best Subsets Regression

Stepwise Regression: Efficiency versus Hospitals, Child_Hosp, ...

```
  Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is Efficiency on 9 predictors, with N = 66


Step                   1       2       3
Constant           106.4   103.3   118.4

AVGE. Distance      -0.503  -0.561  -0.499
T-Value            -4.80   -5.99   -5.59
P-Value            0.000   0.000   0.000

Size 3                      14.7    16.6
T-Value                     4.33    5.16
P-Value                    0.000   0.000

AVGE. Waiting Time                   -0.65
T-Value                            -3.28
P-Value                            0.002

S                   14.6    12.9    12.0
R-Sq               26.47   43.33   51.71
R-Sq(adj)          25.32   41.53   49.38
Mallows Cp          28.6     9.8     1.5
```

Figure E.10: Stepwise Regression

Regression Analysis: Efficiency versus AVGE. Distance, AVGE. Waiting , ...

The regression equation is
Efficiency = 118 - 0.499 AVGE. Distance - 0.649 AVGE. Waiting Time + 16.6 Size 3

Predictor	Coef	SE Coef	T	P
Constant	118.430	5.549	21.34	0.000
AVGE. Distance	-0.49858	0.08927	-5.59	0.000
AVGE. Waiting Time	-0.6485	0.1976	-3.28	0.002
Size 3	16.602	3.214	5.16	0.000

S = 11.9853   R-Sq = 51.7%   R-Sq(adj) = 49.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	9537.6	3179.2	22.13	0.000
Residual Error	62	8906.1	143.6		
Total	65	18443.7			

Source	DF	Seq SS
AVGE. Distance	1	4881.4
AVGE. Waiting Time	1	824.3
Size 3	1	3831.9

Unusual Observations

Obs	AVGE. Distance	Efficiency	Fit	SE Fit	Residual	St Resid
5	37.1	37.43	73.14	3.44	-35.71	-3.11R
6	39.4	56.56	80.46	2.05	-23.90	-2.02R
9	43.4	44.78	74.24	2.64	-29.46	-2.52R
22	86.3	98.23	72.68	5.34	25.55	2.38RX
25	42.0	45.83	75.45	2.52	-29.62	-2.53R
46	15.3	100.00	79.28	5.17	20.72	1.92 X
48	54.7	42.30	67.26	3.33	-24.96	-2.17R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 1.94921

Figure E.11: Regression Analysis

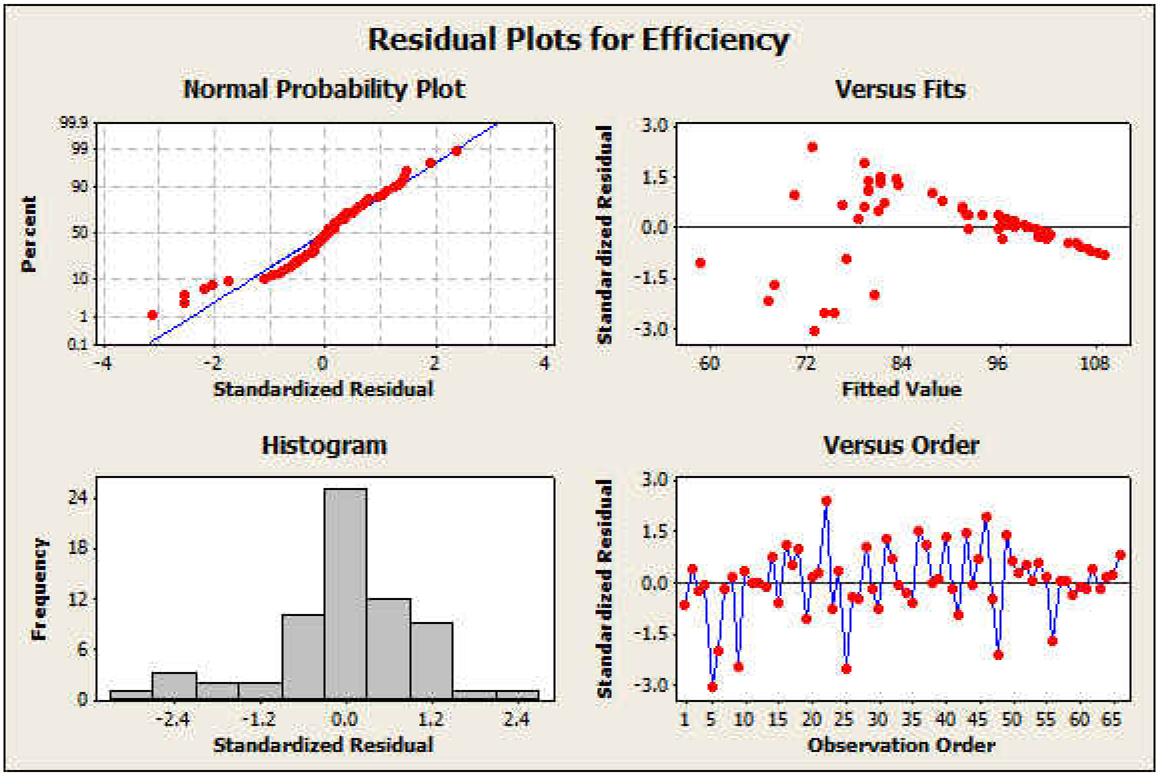

Figure E.12: Residual Plots

APPENDIX F: ORDINAL LOGISTIC REGRESSION

E.1 Ordinal Logistic Regression Model

The ordinal logistic regression allows working with a logistic regression with more than two groups of outcomes, and these groups can be ordered. This regression models the probability of belonging to a specific group. The most common ordinal logistic model is the proportional odds model or also called the cumulative logit model.[45] This relationship is as follow:

$$\frac{Prob(Belonging\ to\ category\ k\ or\ lower)}{Prob(Belonging\ to\ category\ higher\ than\ k)}$$

This model considers that "the probability of belonging to outcome category k or a lower category is compared to belonging to category high than k." (Afifi, May, and Clark, 2012,p.302). However, this method requires a large number of data to get a significant value of the odds, as the literature shows using data set of 400 and up number of elements. For this reason, even though we compute the ordinal logistic regression to analyze the relationship between efficiency and dependent variables selected using only 75 elements, we cannot expect a conclusive analysis for this case.

The data considered for computing the ordinal logistic regression includes five variables independent, and one variable dependent. The variables selected as independent variables are the main variables that describe the hospital network and disaster size features. The independent included variables are number of hospital in each network, average distance among disaster site and hospitals, average services offered for each network, average waiting time of the hospitals

[45] Afifi, A., May, S., & Clark, V. A. (2011). Practical Multivariate Analysis (pp. 269-317) (5th ed.). CRC. Boca Raton.

into the network, and size of the disaster. On the other hand, the dependent variable describes the efficiency, using an efficiency range. This variable takes five values according the level of efficiency (High efficiency: 5, Efficiency: 4, Neutral: 3, No Efficient: 2, and Low Efficient: 1).The complete data set is in Appendix D.

Table F.1: Data Set for Regression Analysis

	Network	Hospitals	Avge. Dist.	ED Beds	Avge. Waiting Time	Size	Rang e	Efficien cy
1	Airport	4	9.05	64	18.16	1	5	98.36
2	Airport	16	15.27	253	29.4	3	5	93.6
3	Amway Center	4	12.86	64	19.24	1	5	98.36
4	Amway Center	11	21.96	157	17.89	2	5	91.33
5	Amway Center	16	22.37	253	29.4	3	4	88
6	Animal Kingdom	4	18.22	62	19.8	1	5	96.77
7	Animal Kingdom	12	27.43	158	19.25	2	5	90.46
8	Animal Kingdom	16	29.36	253	29.27	3	4	84.8
9	Central Florida Regional Hospital	5	53.99	91	20.16	1	1	0
10	Central Florida Regional Hospital	16	68.94	253	29.8	3	1	0
11	Dr. P. Phillips Hospital	9	22.86	156	36.81	2	5	100
12	Dr. P. Phillips Hospital	16	30.95	253	30.68	3	4	80.4
13	Epcot	5	19.94	69	16.58	1	5	100
14	Epcot	12	25.6	170	21.14	2	5	97.09
15	Epcot	16	28.44	253	29.32	3	4	84.8
16	Florida Citrus Bowl Stadium	16	13.61	253	29.4	3	5	100
17	Florida Citrus Bowl Stadium	4	8.72	62	17.84	1	5	98.36
18	Florida Hospital Apopka	6	39.39	91	28.26	1	2	40
19	Florida Hospital Apopka	10	43.36	160	34.81	2	1	13.76
20	Florida Hospital Apopka	16	48.15	253	29.8	3	1	8.4
21	Florida Hospital Celebration	4	27.52	55	26.18	1	5	100
22	Florida Hospital Celebration	10	35.41	163	37.49	2	4	84.43
23	Florida Hospital Celebration	16	43.47	253	29.96	3	3	54.4
24	Florida Hospital East Orlando	4	24.07	71	26.94	1	5	98.36
25	Florida Hospital East Orlando	9	28.79	159	34.25	2	4	86.67
26	Florida Hospital Orlando	10	22.51	174	35.23	2	5	97.41
27	Florida Hospital Orlando	4	17.36	67	46.18	1	5	91.84
28	Florida Hospital Orlando	16	29.34	253	29.84	3	4	86.4
29	Florida Hospital Waterman	6	68.32	74	21.3	1	1	0
30	Florida Hospital Waterman	11	80.39	174	30.09	2	1	0
31	Florida Hospital Waterman	16	86.30	253	29.8	3	1	0

	Network	Hospitals	Avge. Dist.	ED Beds	Avge. Waiting Time	Size	Range	Efficiency
32	Florida Mall	5	13.12	71	16.62	1	5	100
33	Florida Mall	11	19.63	157	17.89	2	5	100
34	Florida Mall	16	19.36	253	29.4	3	5	93.6
35	Health Central	10	30.77	164	36.06	2	5	96.58
36	Health Central	5	26.74	77	40.02	1	4	86.96
37	Health Central	16	36.79	253	29.84	3	4	72.4
38	Hollywood Studios	12	25.14	170	21.14	2	5	97.09
39	Magic Kingdom	12	26.77	164	21.14	2	5	98.35
40	Magic Kingdom	4	18.81	62	19.8	1	5	96.77
41	Magic Kingdom	16	30.61	253	29.27	3	4	84.8
42	Mall At Millennia	11	16.63	157	18.95	2	5	99.9
43	Mall At Millennia	4	9.26	62	17.84	1	5	98.36
44	Mall At Millennia	16	17.21	253	29.4	3	5	90.8
45	Orange County Convention Center	4	11.02	62	17.84	1	5	98.36
46	Orange County Convention Center	11	20.93	157	17.89	2	4	85.33
47	Orange County Convention Center	16	20.73	253	29.27	3	4	84.8
48	Orlando Regional Medical Center	3	15.26	75	48.64	1	5	100
49	Orlando Regional Medical Center	9	19.22	160	34.76	2	5	100
50	Orlando Regional Medical Center	16	27.6	253	29.84	3	4	77.6
51	SeaWorld	10	24.81	144	20.33	2	4	78
52	SeaWorld	16	20.71	253	29.27	3	4	76.4
53	South Lake Hospital	5	48.82	67	20.22	1	2	29.47
54	South Lake Hospital	10	58.91	168	32.57	2	1	9.09
55	South Lake Hospital	16	64.55	253	29.84	3	1	5.6
56	South Seminole Hospital	4	37.14	69	39.32	1	2	26.25
57	South Seminole Hospital	10	41.98	168	33.35	2	1	9.01
58	South Seminole Hospital	16	48.65	253	29.4	3	1	5.6
59	St Cloud Regional Medical Center	4	49.21	55	26.18	1	1	14
60	St Cloud Regional Medical Center	10	54.7	163	36.85	2	1	4.55
61	St Cloud Regional Medical Center	16	62.82	253	29.84	3	1	2.8
62	Universal	11	17.81	157	17.89	2	5	100
63	Universal	4	8.93	62	17.84	1	5	98.36
64	Winter Park Memorial Hospital	10	28.07	166	35.81	2	5	96.58

	Network	Hospitals	Avge. Dist.	ED Beds	Avge. Waiting Time	Size	Range	Efficiency
65	Winter Park Memorial Hospital	4	23.68	67	41.28	1	5	92.31
66	Winter Park Memorial Hospital	16	35.25	253	29.84	3	4	72.4

We perform an ordinal logistic regression analysis using Minitab version 15[46]. The Minitab session window output for the ordinal logistic regression is in Figure E.1. This figure indicates that three of the variables evaluated have low p-value (Distance, Services, and Waiting) and two variables present high p-value (Hospitals and Size). Then, it is possible to conclude, considering $\alpha=0.05$, that the following dependent variables affect the network efficiency level: the average distance in the network, the average services offered in the network, and the waiting time of the hospital in the network. The Log-Likelihood test indicate that there is sufficient evidence to conclude that at least one coefficient is not zero. In addition, the Goodness of Fit tests indicate that we cannot reject the null hypothesis with $\alpha=0.05$, so the model fits the data adequately. If we see the Measures of Association, we can see the summary measures values range from 0.61 to 0.92, which indicates the model fit offers a moderate -to- high level of predictability. However, this moderate -to -high level of predictability is the results of analyze too few elements in this regression.

[46] Minitab academic version can be obtained from http://www.minitab.com/en-US/academic/ (accessed on September 2, 2012)

Ordinal Logistic Regression: Efficiency versus Hospitals, Distance, ...

```
Link Function: Logit
Response Information

Variable    Value  Count
Efficiency  1         15
            2          3
            3          2
            4         18
            5         37
            Total     75

Logistic Regression Table
                                                         95% CI
Predictor        Coef    SE Coef      Z      P   Odds Ratio    Lower
Const(1)    -45.2462    12.3541  -3.66  0.000
Const(2)    -43.7573    12.2568  -3.57  0.000
Const(3)    -42.9358    12.1878  -3.52  0.000
Const(4)    -37.8425    11.4583  -3.30  0.001
Hospitals  -0.760992   0.574867  -1.32  0.186         0.47     0.15
Distance    0.413873  0.0787779   5.25  0.000         1.51     1.30
Services     35.6198    13.5921   2.62  0.009  2.94761E+15  7936.14
Waiting    -0.178156  0.0772056  -2.31  0.021         0.84     0.72
Size         5.31297    3.36890   1.58  0.115       202.95     0.28

Predictor        Upper
Const(1)
Const(2)
Const(3)
Const(4)
Hospitals         1.44
Distance          1.77
Services   1.09479E+27
Waiting           0.97
Size         149642.93

Log-Likelihood = -33.050
Test that all slopes are zero: G = 119.657, DF = 5, P-Value = 0.000

Goodness-of-Fit Tests

Method    Chi-Square   DF      P
Pearson      87.7382  291  1.000
Deviance     66.0992  291  1.000

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs        Number  Percent  Summary Measures
Concordant     1769     95.8  Somers' D              0.92
Discordant       75      4.1  Goodman-Kruskal Gamma  0.92
Ties              3      0.2  Kendall's Tau-a        0.61
Total          1847    100.0
```

Figure F.1: Minitab session window output

```
. margeff

Average partial effects after ologit
      y  = Pr(efficiencylevel)
------------------------------------------------------------------------------
    variable |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
   hospitals |  -.0183107   .0130446    -1.40   0.160    -.0438777    .0072563
  avdistance |   .0099938   .0010802     9.25   0.000     .0078766    .0121111
  avservices |   .8593191   .3673916     2.34   0.019     .1392448    1.579393
avwaitingt~e |  -.0043018   .0018485    -2.33   0.020    -.0079247   -.0006789
        size |   .1390449       .105     1.32   0.185    -.0667512    .3448411
-------------+----------------------------------------------------------------
2            |
   hospitals |  -.0027784    .003131    -0.89   0.375    -.0089152    .0033583
  avdistance |   .0013502   .0012143     1.11   0.266    -.0010297    .0037302
  avservices |   .1194822   .1105782     1.08   0.280    -.0972471    .3362114
avwaitingt~e |  -.0005812   .0005169    -1.12   0.261    -.0015943    .0004319
        size |   .0316209    .026398     1.20   0.231    -.0201183    .0833601
-------------+----------------------------------------------------------------
3            |
   hospitals |  -.0031277   .0036334    -0.86   0.389    -.0102489    .0039936
  avdistance |   .0017997   .0016998     1.06   0.290    -.0015318    .0051311
  avservices |   .1528271   .1192416     1.28   0.200    -.0808822    .3865364
avwaitingt~e |  -.0007747   .0006237    -1.24   0.214    -.0019971    .0004477
        size |   .0207651   .0267269     0.78   0.437    -.0316187    .0731489
-------------+----------------------------------------------------------------
4            |
   hospitals |  -.0284336   .0241801    -1.18   0.240    -.0758258    .0189586
  avdistance |   .0152776   .0049252     3.10   0.002     .0056245    .0249308
  avservices |   1.318795   .6100409     2.16   0.031     .1231371    2.514453
avwaitingt~e |  -.0065762   .0040481    -1.62   0.104    -.0145103    .0013579
        size |    .136419   .0224019     6.09   0.000      .092512     .180326
-------------+----------------------------------------------------------------
5            |
   hospitals |   .0526504   .0408227     1.29   0.197    -.0273605    .1326614
  avdistance |  -.0284213   .0041573    -6.84   0.000    -.0365695   -.0202731
  avservices |  -2.450424   .8848144    -2.77   0.006    -4.184628   -.7162194
avwaitingt~e |   .0122339   .0056559     2.16   0.031     .0011485    .0233194
        size |  -.3278499   .1393502    -2.35   0.019    -.6009713   -.0547285
------------------------------------------------------------------------------
```

Figure F.2: Stata session window output

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