A Multiple Decision-Maker Approach to Allocating Resources to Prepare and Respond to Major Disruptions

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Dedication

I would like to dedicate this thesis to the friends, family, and professors that helped me to complete my journey through my Bachelor's and Master's degrees in Industrial Engineering at Iowa State University. Without the tireless contributions of professors like Dr. Cameron MacKenzie and the rest of my committee, a work like this would not have been possible.

Table of Contents

List of Tables

List of Figures

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Abstract

Disruptions are significant events that cause a disturbance in the normal operations of communities and can result in thousands of fatalities, millions of dollars lost, and significant infrastructure and ecological damage. It is difficult to model the different decision makers in a disruption and express the decisions made in a form that all decision makers understand and can act upon. In disruption response planning, it is necessary to have specific allocation strategies in place, rather than just a set of guidelines, so that budgets can be created, and effective distribution pathways can be established. Therefore, models need to incorporate both specific spending strategies and multiple decision makers. The resource allocation model developed allows for the objectives of four different independent decision makers to be combined into a single computational metric of economic production measured in U.S. dollars. The model provides insight into areas where decision makers may benefit from cooperation to yield larger overall gains in the reduction of production losses from a disruption. The identification of overlaps shows the potential effect of shared decision making in a complex decision environment. The model is applied to a hurricane with magnitude akin to Hurricane Katrina in the context of the 2015 economy of the U.S. Gulf Coast. Results from the application illustrate that there is likely double spending and overspending in some industries in the impacted economic region, and shared decision making between decision makers is highly encouraged. Shared decision making between decision makers allows for a greater benefit to the economic region than when the federal government acts alone.

Chapter 1. Introduction and Literature Review

Disruptions come in many forms and can be minor like traffic jams and unexpected power outages or major like tsunamis or volcanic eruptions. These disruptions cost individuals and organizations time, money, resources, and even lives, making the study of disruptions of high interest to many researchers, enterprises, and government officials. Carter (2008) defines a disruption or disaster as "an event which impacts with such severity that the affected community has to respond by taking exceptional measures." Proper risk mitigation strategies help to prevent some of these disruptions such as terrorist attacks or incidents caused by human error. Other disruptions, like earthquakes and hurricanes, cannot be prevented but risk mitigation strategies can help reduce the consequences from these disruptions. This thesis will focus on non-preventable disruptions like natural disasters although the general model can be applied to preventable disruptions.

Prevention, preparedness, and response have received significant attention in the homeland security and emergency preparedness literature. Some decision makers prefer general strategies that help frame the situation and give rough and flexible guidelines that can be applied to any situation. Farazmand (2001) develops a handbook that is a collection of the various risk management strategies applied over the years. Others attempt to address disruptions by using the classical risk management paradigm (Haimes 1998, Kaplan and Garrick 1981) which emphasizes the identification, measurement, and mitigation of potential risks. Disruptions are not just the focus of researchers and companies but also of the various government organizations across the world. The Disaster Mitigation Act of 2000, which requires all state, local, and Indian Tribal governments within the United States to have written disaster plans in place, and the Federal Emergency Management Agency (FEMA) teaching guide (McEntire 2004), which is required training literature on the theory of emergency management for all FEMA employees, are a few examples. These documents provide general guidelines and strategies without providing a lot of concrete examples backed with empirical data. Seeing the need for more in-depth explanation, researchers have developed specific strategies for individual groups like physicians (Hick 2012) and the tourism industry (Ritchie

2004). Although these strategies provide specifics, they lack the scope of a real disruption. This scope and specificity have been addressed from three different approaches: computational models, qualitative models, and game theory models, all of which have their own strengths and weaknesses to be discussed.

Atlay and Green (2006) examine the disaster operations management literature. They find that approximately 60 of the 109 journal articles analyzed used either mathematical programming, statistics and probabilities, or simulation during their analysis. These approaches make up what are known as computational models, which typically involve data sets, parameterized inputs, or mathematical theory to create a model that gives numerical output. Computational models are often viewed as being empirical, more exact, and better supported than qualitative approaches, but many computational models have the same issue when compared with one another. The vast majority of these computational models assume a single decision maker, usually for the purpose of model or computational simplification. Some models tackle the entire scope of the disruption, but they assume a single, all-powerful decision maker who manages all of the resources and distributes them (Sherali et al. 1991; Barbarosoğlu and Arda 2004). Since every large disruption involves multiple individuals and organizations, modeling a disruption with a single decision maker can provide challenges for applying these disaster operations management models. Other models view resource allocation during disasters as a supply-chain issue (Caunhy 2012, Alp Ertem 2011, Papadakis and Ziemba 2001) or opportunities to minimize death and injury (Friedrich 2000), which may not cover some of the other important aspects of disruptions like housing, utilities, and restoration. Golany (2009) attempts to integrate multiple models in order to solve a resource allocation model, but these models are all to be utilized by a single decision maker, the government. It remains an open research question of how to design operations management models that includes the different perspectives of multiple decision makers.

When trying to model a decision with multiple decision makers, it is important to note that each decision maker has his or her own objectives, motivations, and influences. Multi-Criteria Decision Analysis (MCDA) may be a method to incorporate these elements from multiple decision makers by gathering scores from different decision makers and combining those scores via categorizing, summing, weighting, or multiplying to give an overall utility or value for each consequence (Guitouni and Martel 1998). Other tools are based on the Analytic Hierarchy Process (Saaty 1980). These MCDA techniques have been applied to dealing with disruptions since the attacks of September 11. Applications include using fuzzy optimization and scale factors for resource allocation (Sheu 2005), the Group Analytic Network Process for chemical spills (Levy and Kouichi 2007), and the Analytic Network Process with flooding in Tokai, Japan (Levy et al. 2007). These scores may contain a lot of subjectivity based on the manner in which they are gathered. For example, Geldermann (2009) uses multi-attribute value theory to decide on the optimal alternative for a proposed nuclear/radiological event in Europe, but the inputs were decided as a group rather than the traditional comparison of individual weights. This result touches on one of the two key issues that found within group decision making: weighting leading to subjectivity and inaccuracy as well as evolving an effective group consensus out of different judgements (Yu and Kin 2011). A second open research question that remains is how to design operations management models that incorporate the qualitative aspects of multiple decision makers within introducing bias and subjectivity into the model.

Group dynamics are something that are not discussed in depth in most group decision-making models, but they contain psychological relationships of which modelers should be aware. Barry and Stewart (1997) find that when studying small groups, as the proportion of extroverts increases, the group's focus on the given task decreases. As a result, the group takes longer to make a decision, which can cost large amounts of lives and money during the response phase of disruption management. The mode of communication in a group discussion also influences the decision (Dubrovsky et al. 1991). They discovered that when meeting in person, the status of the group members had a large effect on the direction the group went. Organizations like the federal government that have a large amount of resources may tend to get more of a say in the decisions for disruptions even when smaller organizations and entities may be able to make more effective use of those resources.

Game theory provides another modeling approach to integrate multiple decision makers. Coles and Zhuang (2011) create a decision support framework for the decision-makers during the recovery phase from a disaster. Much of the game theory literature in disaster management focuses on intentional attacks from a terrorist organization that have specific targets or goals in mind. Shan and Zhuang (2013) discuss strategic versus non-strategic attackers with a decision-maker's objective to minimize total impact. Chittaro and Sioni (2015) use psychological theories of group dynamics to explore multiple decision makers acting as a group in reaction to a terrorist incident. All of the people in the decision group have the same end goal, which is not always representative of a real decision when multiple entities are involved.

Communication between decision makers and from the decision makers to other entities in the environment is also very important in disaster management. A main struggle, even in case studies, is creating a decision-making model that involves everyone more so than the actual solving of the problem (Smith and Dowell 2000). Heath (1995) discusses the issues that can arise when communication is poor during the planning phase of disruption response. Poor communication in the wake of the Kobe earthquake in Japan in 1995 led to less effective response efforts. Consensus driven decision making may not be feasible given the time constraints of a disaster situation when considering all of the entities that may have a stake in the decision. This is the basis of a decision made in the application section of this thesis to only include decision makers that have a large amount of influence or resources.

Both preparedness and response decisions are important for properly analyzing disruptions. Response activities are often more expensive than preparation activities because of the scarcity of resources and the difficulty of getting those resources to the intended location. Between 1985 and 2004, the U.S. federal government spent almost 16 times more on response activities than preparation activities (Healy and Malhotra, 2009). Response spending heavily outweighs preparedness spending in several low and middle-income countries at risk for multiple disasters, but preparedness spending in those countries is also on the rise (De la Fuente 2010). This is a promising observation because several other studies have shown the benefits of spending resources on preparedness can greatly outweigh the costs (Rose et al., 2007, Garrett and Sobel, 2003, Healy and Malhotra, 2009, Godschalk et al., 2009).

This thesis combines elements from the several of the models discussed previously in order to create a more realistic decision-making model for allocating resources to prepare and respond to a disruption. Resource allocation models for four different decision makers will be constructed. The first decision maker is the federal government, the second decision maker is the state government, the third decision maker is the private sector, and the fourth decision maker is a non-governmental organization (NGO). Each resource allocation model is presented as optimization model in which a decision maker seeks to minimize or maximize an objective subject to a resource budget constraint. Each decision maker can allocate resources before a disruption and after a disruption. An economic model translates each of the allocation decisions to quantify the economic losses from the disruption. The thesis has three unique contributions to the field of disaster management. The first is the incorporation of four decision makers with different objectives, resources, and effectiveness into a single mathematical model. The second is combining the decisions of each entity into a single economic measure of production to facilitate comparison. The final contribution is quantifying the effect of shared decision making and communication between decision makers. If the decision makers do not coordinate, there will likely be multiple entities allocating resources to the same area, which may be globally inefficient.

The remainder of this thesis will proceed as follows. Chapter 2 will present each of the four resource allocation models. Chapter 3 will apply these decision-making models to a severe hurricane similar to that of Hurricane Katrina in the context of the 2015 economy. This chapter will also discuss the effect that shared decision making between decision makers on the total production losses for the Gulf Coast region. The fourth and final chapter will contain conclusions, insights, and suggestions for future extensions and research.

Chapter 2. Methodology

Each of the decision-making models assumes the allocation of resources are independent, meaning there is no communication between decision makers. This allows for different perspectives within the decision environment with the same end goal in mind. The four perspectives that will be addressed are a federal or overarching government, a smaller state or local government, a large private for-profit entity, and a non-governmental organization (NGO). The federal government entity is characterized by having the most resources and is able to affect all of the industries in the entire economic region. Similarly, the state government entity has a large amount of resources but can only affect the industries within a specified state or locality. The private for-profit entity has the goal of maximizing profits via minimizing the impact of the disaster in its industry. Although private sector companies do have some corporate social responsibility to assist the general public and other industries, quantifying those actions is difficult. Therefore, the private entity can only allocate resources to their specific industry. Lastly the NGO is categorized as a non-profit entity that has humanitarian goals that can affect all of the industries in the entire economic region. This NGO effects the total production losses by using their resources to increase the working population in order to avert further production losses. These four perspectives will come in the form of four different resource allocation models whose results will all be translated into terms of total production losses in the economic region. The following subsections will discuss each of the decision maker models in detail.

The losses that arise from a major disruption may include lost wages, damaged infrastructure, and casualties. The models derived for this analysis will focus on production losses in a region due to a disruptive event such as a natural disaster. The definition of production loss varies from industry to industry, but each of those definitions can be defined in terms of dollars. For instance, Oerke and Dehne (2004) define production losses for crops as crops that have been planted but are unable to be harvested, while Chi et al. (2002) defines production losses in the cattle industry as milk loss, reduced slaughter value, mortality loss, and reproductive loss. Therefore, the model will take these losses only in general terms of dollars lost for purposes of model simplification and flexibility of application.

All four models will be based on the relationships formed in the Interoperability Input-Output Model (IIM). The IIM translates direct production losses in a specific industry as a result of a disruption to the total production losses for the entire economy of interest (Santos and Haimes, 2004, Santos, 2006). Applications of the IIM include damage to the Italian infrastructure (Setola and De Porcellinis, 2007), Hurricane Katrina (Crowther et al., 2007), and the *Deepwater Horizon* oil spill (MacKenzie et al., 2016). Crowther et al. (2007) and MacKenzie et al. (2016) incorporate the IIM into the objective functions of their optimization models, which is the base construct of the decision-making models in this thesis. For the purpose of model simplification and scope, not all of the industries within the IIM can be directly impacted by the decision makers. A focus has been placed on the larger industries in terms of total production in the economic region, but the indirect impact to the smaller industries is still expressed within the IIM. This means that there may be a smaller number of directly impacted industries than there are total industries in the economic region.

All four of the resource allocation models will consider a single disruptive event. The models also assume the disruptive event will occur at most once per year. The disruption directly impacts m industries, where $m \leq n$ and n signifies the total number of industries within the economic region. The normalized interdependency matrix of the IIM is represented by $\mathbf{A}^*$, which notes all the interdependency connections between all n industries. This matrix $\mathbf{A}^*$ is used to create the square matrix $\mathbf{B} = (\mathbf{I} - \mathbf{A}^*)^{-1}$, which is used to form $\mathbf{B}^{(n \times m)}$ allowing for the selection of only the columns in $\mathbf{B}$ that correspond to the m directly impacted industries. The total production losses, via the IIM, is calculated when $\mathbf{x}^{\mathrm{T}}\mathbf{B}^{(\mathrm{n}\times\mathrm{m})}$ is multiplied by a vector $\boldsymbol{c}^*$ that summarizes the direct impact the decision maker will have on the industries. Here $\boldsymbol{x}$ is a vector of length n that represents the normal production of each individual industry in the economic region. When the base IIM structure, $\mathbf{x}^{\mathrm{T}}\mathbf{B}^{(\mathrm{n}\times\mathrm{m})}$, is taken by itself, the dollar loss for each of the m industries if each industry is completely inoperable. Thus the $\boldsymbol{c}^*$ term signifies the impact that the decision maker has on reducing the consequences of the disruption.

2.1 Federal Government Model

The resource allocation model for the federal government decision maker comes from MacKenzie and Al-Kazimi (2017). Equations 1-1 to 1-4 depicts this model where the decision maker's objective is to minimize the expected production losses if a disruption occurs and maximize production gains if no disruption occurs. The annual probability of the disruption is p. A resource budget constraint Z represents the total budget in dollars available to the decision maker to allocate before or after the disruptive event. The decision maker can allocate resources before the disruption (called preparedness) z_p and choose to spend resources to respond to or recover from a disruption if it occurs.

Preparedness will reduce the overall consequences if the disruption occurs. In this model, the consequences of the disruption are expressed by the vector $\boldsymbol{c}^*$ of length m which accounts for the direct impacts in the m industries. The total production losses due to the disruption is expressed when $\boldsymbol{c}^*$ is multiplied by the base IIM structure, $\mathbf{x}^{\mathrm{T}}\mathbf{B}^{(\mathrm{n}\times\mathrm{m})}\mathbf{c}^*$. If the disruption occurs, the decision maker chooses to allocate the remaining resources not spent on preparedness on response and recovery. The decision maker can distribute those resources equally to all the directly impacted industries z_0 with effectiveness k_0, and to an individual industry i via z_i with effectiveness k_i. Resources that would benefit all industries include activities such as clearing roads of debris, establishing telecommunications, and ensuring the supply of electricity and other utilities to the industries. If no resources are allocated to response and recovery, the direct impact to each industry i is expressed via $\hat{c}_i^*$. This $\hat{c}_i^*$ can be reduced by allocating resources to z_p, z_0, or z_i which will reduce the direct impact to the new value c_i^*, where $c_i^* \leq \hat{c}_i^*$ (Equation 1-2). Equation 1-3 states the assumption that the sum of the resources allocated for preparation, allocated to all industries, and allocated to each industry i must be less than the established budget Z. Equation 1-4 is the non-negative constraint illustrating that the resources allocated within the model must be greater than or equal to zero.

If the disruption does not occur, the resources that would have gone for response and recovery can be redistributed elsewhere within the economy. In the case of the federal government, these resources could be devoted to other government programs or be returned to the taxpayers in order to strengthen the economic region. This economic benefit if no disruption occurs is illustrated in the function $g(z_p, Z)$. If all of the resources are spent on preparedness, then $g(Z, Z) = 0$ since no more resources are available. We assume the function $g(z_p, Z)$ is strictly decreasing in z_p, strictly increasing in Z, and non-negative for $z_p \leq Z$. Since the decision maker desires to minimize the expected production losses within the target economy if a disruption occurs and maximize the production gain if no disruption occurs, a negative sign is required in front of $(1-p)g(z_p, Z)$ in order to minimize the objective function. Given the described parameters, the resource allocation model is expressed as:

Minimize	$p\boldsymbol{x}^T\boldsymbol{B}^{(n\times m)}\boldsymbol{c}^* - (1-p)g(z_p, Z)$		(1-1)
subject to	$c_i^* = \hat{c}_i^* \exp(-k_{qp}z_p - k_0 z_0 - k_i z_i)$	$i = 1, \ldots, m$	(1-2)
	$z_p + z_0 + \sum_{i=1}^{m} z_i \leq Z$		(1-3)
	$z_p, z_0, z_i \geq 0$	$i = 1, \ldots, m$	(1-4)

The model can be applied to any length of time, but we solve the model for a single calendar year. The model also assumes that the consequences of the disruption are reduced via an exponential function. This approach mimics other applications from the risk management literature (MacKenzie et al., 2016) that explore the benefits and drawbacks of various allocation functions. The exponential function is used because it encompasses the concept of diminishing marginal returns. The first dollar spent to reduce c_i^* produces more benefit than the next dollar.

2.2 State or Local Government Model

The state government model has the same form as that of the federal government as depicted in Equations 2-1 to 2-4. However, the parameter values may differ, and we write a superscript (s) to represent the parameters for the state decision maker. Since the size of state economy is smaller than the regional economy (which is of concern to the federal decision maker), the values in the IIM matrix $\mathbf{B}^{(s)(n\times m)}$ and the production vector $\mathbf{x}^{(s)}$ will change. The municipal and federal spending in Switzerland differs, which suggests there is a difference in the effectiveness of spending between the federal and state governments (Joumard and Giorno 2002). Since state governments are presumably closer to the impacted areas, they may have special programs and agencies that are in a better situation to assist in disaster management. The state government model will still contain the same n total industries and m directly impacted industries, but the output results of the model will be different.

$$
\begin{array}{lllr}
\text{minimize} & p^{(s)}\mathbf{x}^{(s)^T}\mathbf{B}^{(s)(n\times m)}\mathbf{c}^{*(s)} - \left(1-p^{(s)}\right)g^{(s)}(z_p^{(s)}, Z^{(s)}) & & \text{(2-1)} \\
\text{subject to} & c_i^{*(s)} = \hat{c}_i^{*(s)} \exp(-k_p^{(s)} z_p^{(s)} - k_0^{(s)} z_0^{(s)} - k_i^{(s)} z_i^{(s)}) & i = 1, \dots, m & \text{(2-2)} \\
& z_p^{(s)} + z_0^{(s)} + \sum_{i=1}^{m} z_i^{(s)} \le Z^{(s)} & & \text{(2-3)} \\
& z_p^{(s)}, z_0^{(s)}, z_i^{(s)} \ge 0 & i = 1, \dots, m & \text{(2-4)}
\end{array}
$$

2.3 Private Sector Model

The private sector model allocates resources to maximize system resilience (MacKenzie and Zobel 2016). Since the private sector entity is categorized as a for-profit entity, we assume the private sector decision maker desires to maximize the resilience of its firm or industry. Resilience is defined as the ability to withstand a disruption and bounce back or recover from a disruption. The measure of resilience is based on the resilience triangle (Bruneau et al., 2003) where $R = 1 - XT/T^*$ where R is the resilience (ranges between 0 and 1.0), X is the initial loss in system performance in proportional terms, T is the time to recovery, and T^* is the maximum time to recovery (Zobel and Khansa, 2012).

The decision maker can allocate resources for hardening activities z_X or response activities z_T, and these resources would be allocated before a disruption occurs. Resources allocated for hardening activities reduce the initial losses according to the function $X(z_X) = \hat{X} - a_X \log(1 + b_X z_{\bar{X}})$ where $\hat{X}$ is the initial losses if no resources are allocated to hardening, and a_X and b_X are parameters describing the effectiveness of allocating resources. Resources allocated for recovery reduce the time to full performance in a similar manner, $T(z_T) = \hat{T} - a_T \log(1 + b_T z_T)$ where the parameters $\hat{T}$, a_T, and b_T have a similar meaning as the hardening resource allocation function. Interested readers are referred to MacKenzie and Zobel (2016) for further details. Any money not allocated to increase resilience $Z^{(P)} - z_X - z_T$, where $Z^{(P)}$ is the overall budget for the private sector entity, can be reinvested to help the private sector entity improve its profitability. The function describing the effect of the private sector's reinvestment option is $g^{(P)}(z_X + z_T, Z^{(P)})$. Like the previous models, the annual probability of the disruption is $p^{(P)}$, which could be different than the probability for the state or federal government. Therefore, the resource allocation model for the private sector model is expressed as:

$$\text{maximize} \quad p^{(P)}\left(1 - \frac{\left(\hat{X} - a_X \log(1 + b_X z_{\bar{X}})\right)\left(\hat{T} - a_T \log(1 + b_T z_T)\right)}{T^*}\right) + (1 - p^{(P)})g^{(P)}(z_X + z_T, Z^{(P)}) \tag{3-1}$$

$$\text{subject to} \quad z_X + z_T \le Z^{(P)} \tag{3-2}$$

$$z_X, z_T \ge 0 \tag{3-3}$$

After this optimization is solved, we can calculate the private sector's resilience R. Because we desire to translate the private sector's allocation of resources to the economic impacts of the region, we translate the private sector's resilience to direct impacts in order to assess the economic impact and combine the private sector's allocation with the state and federal governments. We assume that resilience R is a linear function of c_i^* so that $R = \beta_0 + \beta_1 c_i^*$ where β_0 and β_1 are parameters and c_i^* are the direct impacts for industry i that corresponds to the private sector industry. Since perfect resilience $R = 1$ corresponds to no direct impacts, i.e., $c_i^* = 0$, then $\beta_0 = 1$. We solve $\beta_1 = \frac{\hat{R}-1}{c_i^*}$ where $\hat{R}$ is the private sector's initial resilience before any resources are allocated. After resources are allocated, the direct impacts are calculated $c_i^{*new} = \frac{R-1}{\beta_1}$. Incorporating this value into the IIM model reveals that the production losses from the disrupted private sector are: $\mathbf{x}^{\mathrm{T}}\mathbf{B}^{(\mathrm{n}\times 1)}c_i^{*new}$ where $\mathbf{B}^{(n\times 1)}$ is a column vector of length n taken from $\mathbf{B}^{(n\times m)}$ where the column corresponds to industry i.

2.4 Non-Governmental Organization Model

Non-profit NGOs are often neglected when planning for disruption preparedness, response, and recovery. These organizations devote resources, aid, and personnel to a region impacted by a disruption in the hopes of minimizing deaths and injuries while maximizing the welfare of the citizens within the region. An NGO is not interested in maximizing its profit, and it can be difficult to quantify the NGO's contribution to specific industries as in the federal and state government models. The NGO's contributions do make a difference in the recovery efforts of a disruption. These differences come in the form of increased public welfare, reduced time to full recovery, and helping the impacted region's workforce. Therefore, the model representing the NGO decision makers will have the objective of maximizing the available workforce through the allocation of resources like food, relief items, and overnight shelter stays. This is based on the assumption that as the amount of available resources increases, the available workforce will also increase although that may not always be the case in reality.

The model for the NGO assumes a multi-attribute value function, where the decision maker receives value from providing food, relief items, and shelter to the populace impacted by a disruption (Keeney and Raiffa, 1976; Keeney,1996). The NGO determines: y_1 the amount of food procured before the disruption, y_2 the number of relief items procured before the disruption, y_3 the amount of food procured after the disruption, y_4 the number of relief items procured after the disruption, and y_5 the number of shelters provided after the disruption. Food and relief items can be procured before and after the disruption, but shelter can only be procured after the disruption occurs. The NGO's value from distributing food is given the function $v_1(y_1 + y_3)$, the value from distributing from relief items is $v_2(y_2 + y_4)$, and the value from providing shelter is $v_3(y_5)$. The range of each value function is [0,1]. We assume to the total value to the NGO from providing this relief is given by Equation 4

$$\begin{aligned} f(y_1 + y_3, y_2 + y_4, y_5) &= w_1 v_1(y_1 + y_3) + w_2 v_2(y_2 + y_4) + w_3 v_3(y_5) + (1 - w_1 - w_2 \\ &\quad - w_3) v_1(y_1 + y_3) v_2(y_2 + y_4) v_3(y_5) \end{aligned} \tag{4}$$

where $w_1, w_2,$ and w_3 are the trade-off weights—where each weight ranges between 0 and 1—for each of the three value functions. The product term at the end of Equation 4 recognizes that providing food, relief, and shelter could be complements or substitutes for each other. Typically, $w_1 + w_2 + w_3 < 1$, which signifies that food, relief, and shelter are complements and that an NGO should be incentivized to have value for each attribute (Clemen and Reilly, 2001).

As given in Equation 5-1, the NGO seeks to maximize the expected value of providing relief after the disruption where the annual probability of the disruption for the NGO is $p^{(N)}$. If no disruption occurs, the NGO's value $h(y_1, y_2)$ is a function of the food and relief items procured before the disruption. Each of the decision variables has a cost in dollars as depicted by $a_j \geq 0$ where $j = 1,2, \dots, 5$. We assume the cost of procuring a resource after the disruption has occurred is more than procuring the resource before the disruption. Equation 5-3 calculates the NGO's value if no disruption occurs $h(y_1, y_2) = \left(Z^{(N)} - a_1 y_1 - a_2 y_2\right)/Z^{(N)}$ where $Z^{(N)}$ is the NGO's budget. This linear value function assumes that the NGO's value equals 1 if no money is spent preparing for a disruption that does not occur and the NGO's value equals 0 if the entire budget is spent preparing for a disruption that does not occur. Equation 5-4 illustrates that the cost of the resources must be less than or equal to the NGO's budget $Z^{(N)}$. Equation 4-5 reflects the assumption that the number of resources procured and distributed must be greater than or equal to zero. The NGO determines the food, relief items, and shelter to procure and distribution in order to maximize its total expected value.

$$\text{maximize} \quad p^{(N)} f(y_1 + y_3, y_2 + y_4, y_5) + \left(1 - p^{(N)}\right) h(y_1, y_2) \tag{5-1}$$

$$\text{subject to} \quad f(y_1 + y_3, y_2 + y_4, y_5) = w_1 v_1(y_1 + y_3) + w_2 v_2(y_2 + y_4) + w_3 v_3(y_5) + (1 - w_1 - w_2 - w_3) v_1(y_1 + y_3) v_2(y_2 + y_4) v_3(y_5) \tag{5-2}$$

$$h(y_1, y_2) = \frac{Z^{(N)} - a_1 y_1 - a_2 y_2}{Z^{(N)}} \tag{5-3}$$

$$\sum_{j=1}^{5} a_j y_j \leq Z^{(N)} \tag{5-4}$$

$$y_j \geq 0 \qquad for\ j = 1, \dots, 5 \tag{5-5}$$

As with the previous three models, we desire to map the NGO's decisions to economic impact in the region. Since the NGO's decisions provide support and relief to people, we assume the NGO's efforts increase the availability of the workforce, or reduces the unavailability of the workforce, after the disruption. As described by Orsi and Santos (2010), γ_i represents the number of people days of labor made available to industry i, and $Workforce_i$ is the size of the workforce in industry i in the economic region. This value of γ_i is calculated as a function of how much food, relief items, and shelter stays can be distributed given the initial NGO budget. For instance, six meals, two relief items, or a shelter stay may be required in order to contribute two people days of labor, depending on how his/her life was affected by the disruption. In this case, γ_i would be calculated as the sum of 1/6 of the food distributed, ½ of the relief items distributed, and each of the shelter stays provided. The local area personal income (LAPI) is the income of all the people working in each industry i, and x_i remains the production of industry i (as in the IIM). Equation 6 uses these parameters to calculate d_i, the economic benefit of the increased working population in proportional terms for industry i.

$$d_{\boldsymbol{i}} = \frac{(\frac{\gamma_{\boldsymbol{i}}}{365})}{Workforce_i} * \frac{LAPI_i}{x_{\boldsymbol{i}}} \tag{6}$$

After calculating d_i for each of the m industries to obtain the vector **d**, the economic benefits (or the production losses averted) from the NGO's decision can be calculated $\mathbf{x}^T\mathbf{B}^{(n\times m)}\mathbf{d}$.

Chapter 3. Application to Hurricane Katrina

The models are applied to a hypothetical hurricane of the approximate size and scope of Hurricane Katrina. Hurricane Katrina was a Category 5 hurricane that hit the Gulf Coast region of the United States in 2005. It was one of the deadliest and most costly hurricanes in U.S. history. Between 1,245 and 1,836 people died as a result of the hurricane (Beven et al., 2008, Brunkard et al., 2008) with a majority of those deaths being recorded in New Orleans. Hallegatte (2008, 2011) estimates the losses from Hurricane Katrina between $74 and $149 billion to local business and recovery and reconstruction of the area to cost the federal government between $75 and $110 billion.

The federal government will consider the five states surrounding the Gulf of Mexico, Alabama, Florida, Louisiana, Mississippi, and Texas. The state government decision maker is Louisiana, which was the state that was most impacted by Hurricane Katrina. The private sector decision maker is the utilities industry (which will be assumed to be a single decision maker), and the NGO is the American Red Cross. As was mentioned in the introduction, the results from Heath (1995) suggest that only the decision makers with a large amount of resources or influence should be considered in decision-making models. This is because the smaller entities are not always able to get their voice heard and can introduce more complications and time to the decision. Although it is possible to apply the developed models to any sized entity. The results of each of these models are expressed in terms of expected economic losses from the disruptions. These economic losses ignore casualties and environmental damage, except to the extent that those factors influence the economic loss in individual industries and the economic region as a whole.

The parameters in each of the models are estimated from government databases, media stories, and journal articles and have been brought into terms of 2015 dollars via the general inflation rate if needed. The IIM is populated with data from the U.S. Bureau of Economic Analysis (2015). This data results in an aggregated target economy for the Gulf States with n =63 industries which are used to populate the $\mathbf{x}$ and $\mathbf{B}$ vectors considered in all four models. We assume the hurricane directly impacts m=32 of those industries. The data used in the following models for parameters like losses due to the disruption, the recovery time of each industry, and the impact of each industry on the other industries in the decision environment are based on data gathered in MacKenzie and Al-Kazimi (2017). In most cases where solid recovery time data is not available, it is assumed that it would take each industry 10 years to fully recover from the hurricane if no resources were allocated to the region. It is possible that some industries might never recover from such an event, but this assumption helps to simplify the calculations. Comparisons between the models are made in an attempt to simulate a situation in which the individual decision makers collaborate with one another to reach a better end result.

3.1 Application of the U.S. Federal Government

The parameter estimations that are used for the federal government resource allocation model are described in this section along with the results that these parameters yield. Tourism makes up the first four industries in this model, seeing as they were so severely impacted by the hurricane. The industries in the middle of the matrix, $i = 5,6, \dots, 25$, represent the industries that were directly impacted by the hurricane due to damage to raw materials, production facilities, offices, etc. (Hallegatte, 2008). These 21 middle industries make up a large portion of the private sector in this model. The reminder of the industries are illustrated in Table 1 with a description of each industry and its associated index i. Since the model for the federal government is derived from the model in MacKenzie and Al-Kazimi (2017), the origins of the impact parameters $\hat{c}_i^*$ and effectiveness parameters k_i for each of the industries is explain in detail in that paper. The Gross Domestic Product (GDP) values from their analysis has been substituted with the GDP values from 2015 and the cost values have been inflated to 2015 costs using the general inflation equation.

Table 1: Input Parameters for Federal Government Model

$\boldsymbol{i}$	**Industry**	$\boldsymbol{\hat{c}_i^*}$	$\boldsymbol{k_i}$ (per $1 million)
1	Retail trade	0.0032	0.0149
2	Amusements	0.0193	0.0262
3	Accommodations	0.0128	0.0259
4	Food services	0.0119	0.00904
5	Farms	0.0225	0.000912
6	Fishing and forestry	0.0225	0.005915

7	Construction	0.0225	0.000172
8	Wood products	0.0225	0.00306
9	Nonmetallic minerals	0.0225	0.002043006
10	Primary metals	0.0225	0.001514286
11	Fabricated metals	0.0225	0.000871633
12	Machinery	0.0225	0.000718841
13	Computer and electronics	0.0225	0.000933636
14	Electrical equipment	0.0225	0.004205973
15	Motor vehicles	0.0225	0.000505622
16	Furniture	0.0225	0.00421429
17	Miscellaneous manufacturing	0.0225	0.00313142
18	Food and beverage	0.0225	0.000478338
19	Textile	0.0225	0.007987559
20	Apparel	0.0225	0.015357594
21	Paper	0.0225	0.001654325
22	Printing	0.0225	0.005544869
23	Chemical products	0.0225	0.000280555
24	Plastics and rubber products	0.0225	0.001674454
25	Wholesale trade	0.0225	0.000154338
26	Utilities	0.0023	0.014402372
27	Water transportation (ports)	0.0171	0.003557337
28	Education	0.0270	0.010977419
29	Oil and gas	0.0662	0.000259584
30	Petroleum products	0.0402	0.000259584
31	Federal government	0.0257	0.000411337
32	State government	0.0370	0.000411337
Prevention		$k_p = 0$	
Preparedness		$k_q = 1.6 \times 10^{-4}$	
All industries simultaneously		$k_0 = 1.0 \times 10^{-5}$	
Initial probability		$p = 0.56$	

The probability of a hurricane occurring is estimated as p, and was derived from the Hurricane Research Division (2015) report that 25 hurricanes of Category 2 or more struck at least one of the Gulf States between 1970 and 2014, with the remaining 21 hurricanes being weaker than a Category 2. Considering that the consequences of this federal government model attempt to replicate the scale of Hurricane Katrina, the probability of a hurricane occurring is likely overestimated. The values of k_q and k_0 are estimated by the comprehensive cost-benefit analysis of preparedness and response money by Healy and Malhotra (2009), which estimates that money spent on preparedness is 15 times more effective than on response.

With the model parameters set, the resource allocation model is solved for budgets ranging from Z = $0 to $50 billion. The fmincon function within Matlab is used to solve the optimization problem. The results of this optimization are illustrated in Table 2. The results of the model show that it is most of the money spent by the federal government should be spent on preparing for the disruption in order to reduce the impact of the disruption. This is not a surprising result considering the large difference in effectiveness between preparedness spending and response spending. Spending on individual industries does not start to become highly advised until the budget exceeds $25 billion. At that point, the money spent on preparation starts to decrease because the budget gets so large that it is more beneficial to reinvest the resources into the economic region and respond to the disruption if it occurs.

Table 2: Optimal Federal Resource Allocation for Different Budgets (millions of dollars)

Industry	Budget					
	5,000	**10,000**	**20,000**	**30,000**	**40,000**	**50,000**
Pre-disruption	4918	9851	14223	12933	11156	9365
All industries	0	0	0	0	0	0
Retail trade	18	32	126	174	194	213
Amusements	13	21	74	102	113	124
Accommodations	11	19	73	100	112	123
Food services	40	63	217	297	330	362
Farms	0	0	0	255	592	900
Fishing and forestry	0	0	0	0	31	78
Construction	0	0	0	652	2310	3977
Wood products	0	0	0	106	204	296
Nonmetallic minerals	0	0	0	97	245	378
Primary metals	0	0	0	205	401	593
Fabricated metals	0	0	0	278	620	949
Machinery	0	0	0	347	774	1141
Computer and electronics	0	0	0	0	168	500
Electrical equipment	0	0	0	43	114	180
Motor vehicles	0	0	0	741	1320	1866
Furniture	0	0	0	62	137	192
Miscellaneous manufacturing	0	0	0	38	129	238
Food and beverage	0	0	0	604	1209	1791
Textile	0	0	0	33	70	106
Apparel	0	0	0	15	34	53
Paper	0	0	0	194	373	543
Printing	0	0	0	32	86	137
Chemical products	0	0	0	588	1666	2705
Plastics and rubber products	0	0	0	173	352	517
Wholesale trade	0	0	0	0	1423	3121

Utilities	0	0	14	64	85	104
Water transportation (ports)	0	0	3	206	290	372
Education	0	14	142	207	235	261
Oil and gas	0	0	0	765	1933	3058
Petroleum products	0	0	2811	5594	6777	7892
Federal government	0	0	0	1013	1718	2404
State government	0	0	2317	4079	4798	5462

Figure 1 depicts the expected production losses as a function of federal budget ranging from $0 to $50 billion. The expected production losses appear to follow an exponential curve where increases in budgets past $20 billion have little effect on further decreasing the expected production losses. Since most of the allocation functions in the model are exponential based on the exponential model with diminishing marginal returns and the aggregate of many exponential functions is also an exponential function.

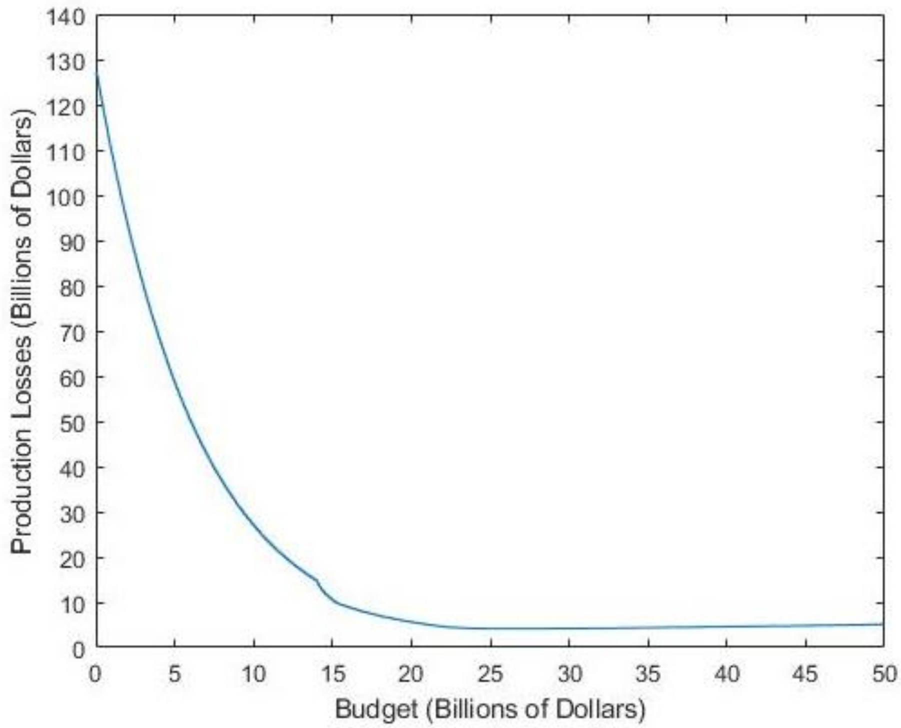

Figure 1: Expected Production Losses to Gulf States

3.2 Application of the State of Louisiana

Table 3 depicts the input parameters for the Louisiana state government resource allocation model. We assume the state government's effectiveness parameters for industry i, $k_i^{(s)}$, is two times larger than that of the federal government, i.e., $k_i^{(s)} = 2k_i$. This assumption reflects that Louisiana has more knowledge than the federal government about what individual industries require and can more easily help those industries recover. The choice of Louisiana being twice as effective as the federal government is arbitrary considering that there is no published number definitively stating the difference in effectiveness between governments. Any reasonable number between 0.5 and 4 could have been used in this situation, but 2 allows for a differentiation between the state and federal government models other than the size of their respective available budgets. Since the direct impacts for industry i $\hat{c}_i^*$ is a proportion of the damage to the industry's entire production, $\hat{c}_i^{*(s)} > \hat{c}_i^*$ because an industry's entire production in Louisiana is less than the industry's entire production in the five Gulf states and most of the direct impacts from the hurricane occur in Louisiana. Since Louisiana is one of the five Gulf States, the probability that a hurricane hits is taken as one fifth the overall probability of a hurricane hitting the Gulf.

Table 3: Input Parameters for State Government Model

i	**Industry**	$\hat{c}_i^*$	k_i (per $1 million)
1	Retail trade	0.041788	0.029835
2	Amusements	0.253523	0.052305
3	Accommodations	0.123939	0.05184
4	Food services	0.164857	0.018087
5	Farms	0.196876	0.002795
6	Fishing and forestry	0.196876	0.009038
7	Construction	0.196876	0.000331
8	Wood products	0.196876	0.003933
9	Nonmetallic minerals	0.196876	0.004927
10	Primary metals	0.196876	0.004061
11	Fabricated metals	0.196876	0.001586
12	Machinery	0.196876	0.00168
13	Computer and electronics	0.196876	0.024414
14	Electrical equipment	0.196876	0.022839
15	Motor vehicles	0.196876	0.018653
16	Furniture	0.196876	0.042128
17	Miscellaneous manufacturing	0.196876	0.013764
18	Food and beverage	0.196876	0.000876
19	Textile	0.196876	0.029433
20	Apparel	0.196876	0.132251
21	Paper	0.196876	0.001218
22	Printing	0.196876	0.017431
23	Chemical products	0.196876	0.000243
24	Plastics and rubber products	0.196876	0.005817

25	Wholesale trade	0.196876	0.000431
26	Utilities	0.021222	0.028805
27	Water transportation (ports)	0.058827	0.007115
28	Education	0.286347	0.021955
29	Oil and gas	0.04	0.000519
30	Petroleum products	0.062126	0.000519
31	Federal government	0.026	0.000823
32	State government	0.464904	0.000823
Prevention		$k_p = 0$	
Preparedness		$k_q = 1.6 \times 10^{-4}$	
All industries simultaneously		$k_0 = 1.0 \times 10^{-5}$	
Initial probability		$\hat{p} = 0.11$	

Table 4 depicts the optimal allocation for budgets ranging from \$5 to \$50 billion. The results show that the state government will start to spend on individual industries sooner than the federal government. The results also show that the state government should not spend any money on preparation for the hurricane. This is a very surprising result considering that the state effectiveness is only two times more effective than that of the state. It is possible that since the state budget will likely be much smaller than the federal government it is better to target individual industries so that the economic region can start to generate income faster. This could allow the overall impact to the state to be much smaller. It may also be the case that since the economy of Louisiana is so much smaller than the entire Gulf Coast economy that there may not have been as much damage to recover from.

Table 4: Optimal State Resource Allocation for Different Budgets (Millions of Dollars)

Industry	Budget					
	5,000	**10,000**	**20,000**	**30,000**	**40,000**	**50,000**
Pre-disruption	0	0	0	0	0	0
All industries	0	0	0	0	0	0
Retail trade	95	106	124	143	156	181
Amusements	56	61	72	83	93	99
Accommodations	55	61	72	83	95	97
Food services	163	180	211	243	269	295
Farms	36	146	346	529	774	921
Fishing and forestry	0	15	77	139	197	305
Construction	4	929	2645	4392	6041	7445
Wood products	60	138	280	420	546	599
Nonmetallic minerals	17	79	193	298	424	529
Primary metals	33	108	247	381	510	563
Fabricated metals	58	251	604	967	1364	1617

Machinery	40	223	560	892	1313	1535
Computer and electronics	0	1	24	47	70	99
Electrical equipment	1	14	39	63	88	176
Motor vehicles	0	17	47	74	104	121
Furniture	2	9	23	36	51	65
Miscellaneous manufacturing	0	20	61	103	134	242
Food and beverage	160	509	1152	1763	2297	3066
Textile	4	14	33	52	68	86
Apparel	0	3	7	11	15	21
Paper	193	445	901	1380	1709	2171
Printing	3	21	53	91	128	144
Chemical products	323	1585	3884	6121	8198	9864
Plastics and rubber products	30	83	179	279	386	512
Wholesale trade	0	286	1587	2955	4276	5436
Utilities	23	34	54	71	93	116
Water transportation (ports)	138	181	260	339	399	478
Education	115	129	155	182	223	229
Oil and gas	0	0	0	0	0	187
Petroleum products	1033	1623	2693	3791	5002	6436
Federal government	0	0	0	0	72	547
State government	2356	2728	3416	4073	4907	5817

Figure 2a depicts the expected production losses in the state of Louisiana as budget increases from \$0 to \$50 billion. The shape of the line is similar to that of the federal government model, which is expected since the model calculations are based on the same exponential principals. However, the magnitude of the losses is only 2/3 of the federal government. The diminishing marginal returns also appears to take effect much quicker than in the federal government case. This is a promising result since the budget of the state government would likely be much smaller than the federal government. As mentioned at the start of this subsection, there is some ambiguity in the relative effectiveness between the state and federal governments. Figure 2b depicts the results of the model if the effectiveness of state spending is considered to be equal to that of the federal government, given all other model inputs remain the same. When comparing Figures 2a and 2b, the impact of effectiveness on production losses becomes clearer. Having an increased effectiveness brings the knee of the curve closer to the y-axis and the asymptote of the curve approaches the x-axis. This means that as effectiveness increases, smaller budgets have a slightly larger impact and more production losses can be averted as budgets become large. If the state is less effective than the federal government, the opposite result is expected.

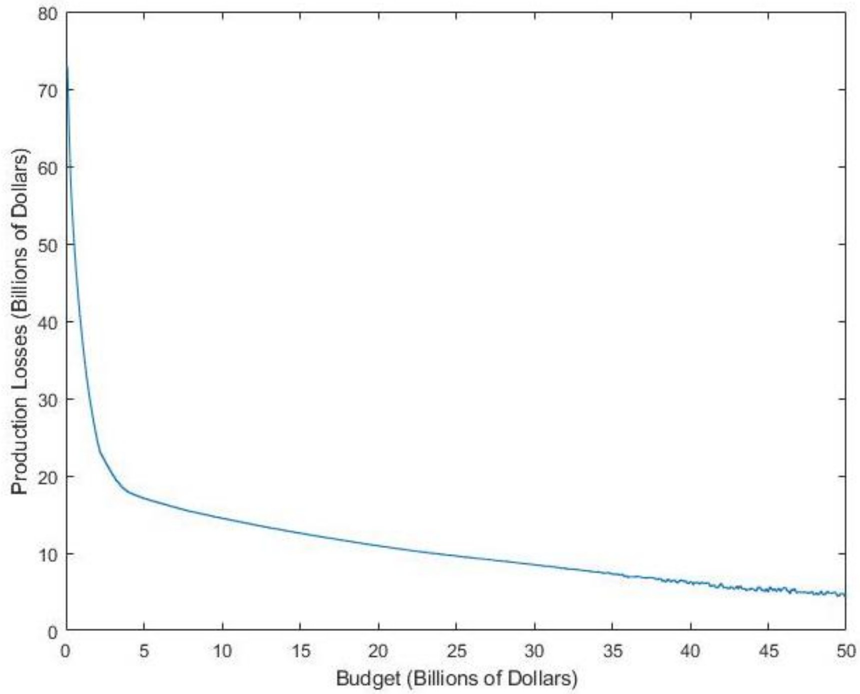

Figure 2a: Expected Production Losses to State of Louisiana Double Effectiveness

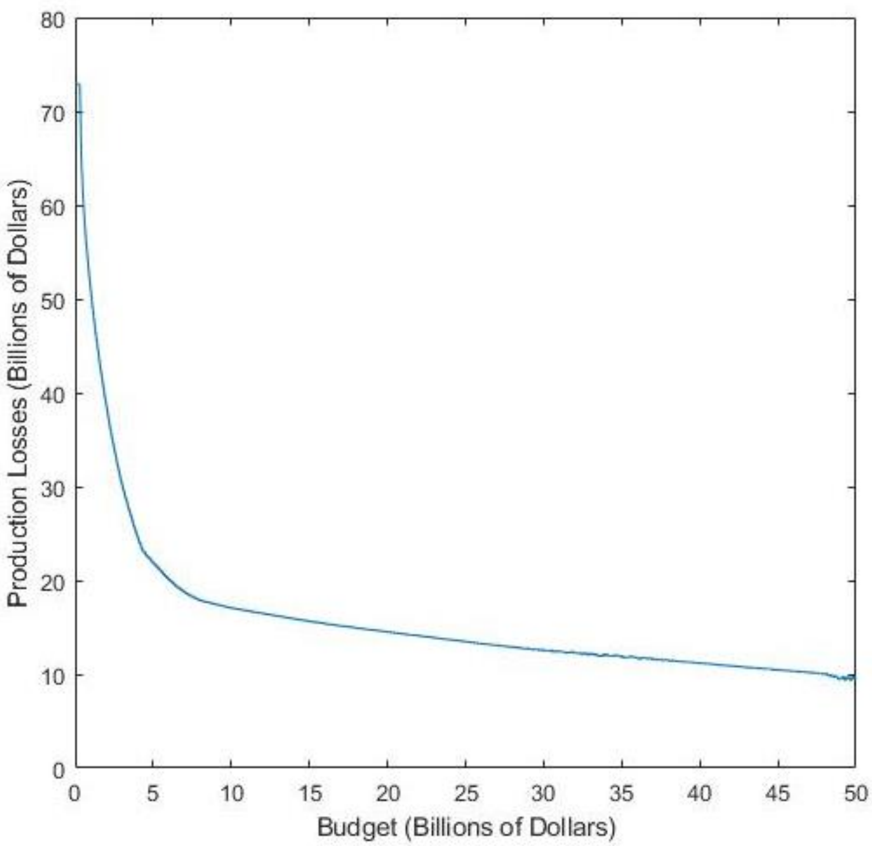

Figure 2b: Expected Production Losses to State of Louisiana Nominal Effectiveness

3.3 Application of the Utilities Companies

Many private sector companies were impacted by Hurricane Katrina from small businesses that employ a handful of people to large businesses that employ thousands. The private sector model described earlier can be applied to any type of business, but the goal of this specific application is to use a company that has a large scope and impacts many of the other industries within the economy. Therefore, a utility company that services all of Louisiana was selected due to the revenue it produces and its ability to assist the other industries and entities. Although utilities companies are part of a regulated industry, their use within this model works because they remain a for profit entity that has a large number of resources and can affect multiple other industries. Their regulation also allows for more data being available on the quantity of resources and the use of those resources when compared to other privately held for profit entities. This allows for the creation of a more accurate model and decision environment. After Hurricane Katrina hit the Gulf Coast, as much as 30% of Louisiana was without power along with smaller portions of neighboring Mississippi and Alabama (Crowther et al., 2007). It took three to four months for power to be restored to all of the customers in the region.

The input parameters for the resilience of the utilities' companies model are taken from MacKenzie and Zobel (2016), and the impact of the disruption in the utilities' industry are taken from Crowther et al. (2007). Based on these papers, the initial post-disruption resilience of the utilities sector in Louisiana is estimated as 0.737, and the maximum budget a utilities company would have available for this situation is $1 billion. The remainder of the input parameters used in Equations (3-1) to (3-3) are depicted in Table 5.

Table 5: Input Parameters for Utilities Model

$\hat{X} = 0.63$	$a_X = 0.055$	$b_X = 30$
$\hat{T} = 45$	$a_T = 0.9$	$b_T = 3.6$

Table 6 depicts the allocation of resources for hardening z_X and recovery z_T activities for a budget ranging from $0 to $1 billion, the resilience of the system, and c_i^{*new} that is generated from the utilities' resilience. The results show that although the budget continues to increase, once the budget reaches $150 million the spending on hardening activities and response stops increasing. At that point, it is better to spend any of the remaining budget on other priorities not related to resilience for the utility company.

Table 6: Results of Utilities Model

Budget (millions)	Hardening (millions)	Recovery (millions)	Resilience	c_i^{*new}
$0	$0.00	$0.00	0.6850	0.0254
$50	$46.16	$3.84	0.8902	0.0088
$100	$93.26	$6.74	0.9095	0.0073
$150	$115.60	$7.92	0.9153	0.0068
$200	$115.60	$7.92	0.9153	0.0068
$250	$115.60	$7.92	0.9153	0.0068
$300	$115.60	$7.92	0.9153	0.0068
$350	$115.60	$7.92	0.9153	0.0068
$400	$115.60	$7.92	0.9153	0.0068
$450	$115.60	$7.92	0.9153	0.0068
$500	$115.60	$7.92	0.9153	0.0068
$550	$115.60	$7.92	0.9153	0.0068
$600	$115.60	$7.92	0.9153	0.0068
$650	$115.60	$7.92	0.9153	0.0068
$700	$115.60	$7.92	0.9153	0.0068
$750	$115.60	$7.92	0.9153	0.0068
$800	$115.60	$7.92	0.9153	0.0068
$850	$115.60	$7.92	0.9153	0.0068
$900	$115.60	$7.92	0.9153	0.0068
$950	$115.60	$7.92	0.9153	0.0068
$1,000	$115.60	$7.92	0.9153	0.0068

Figure 3 depicts the resilience of the system as the budget increases from $0 to $1 billion. The shape of the graph aligns with the idea of diminishing marginal returns in the as the budget increase the amount the system resilience increases grows at a decreasing rate until the budget reaches approximately $150 million. This leveling off of the resilience reflects the results shown in Table 6 and is caused by a limitation in the production of the utilities company in the state of Louisiana. The production used in this model is based on the Gross Domestic Product (GDP) of the utilities company in Louisiana. If this value was increased in the model to the GDP of the entire five state region, the resilience of the system was able to get closer to 0.95 before reaching a similar plateau before the budget reaches $1 billion. System resilience is related to overall system reliability which means that resilience can never exceed 1.

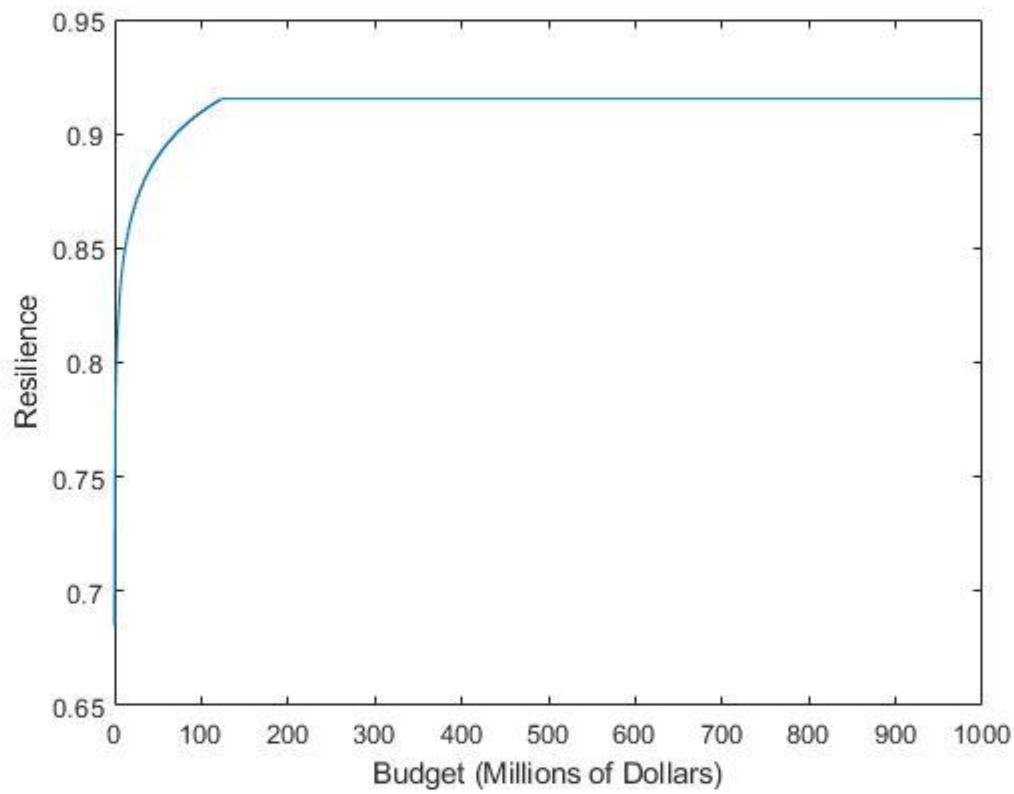

Figure 3: System Resilience as a Function of Budget

Figure 4 depicts the production losses to the Gulf Region from a hurricane as a function of the utilities sector's budget. As the budget increases, the production losses decrease but at a diminishing rate due to the logarithmic nature of the allocation functions for $X(z_X)$ and $T(z_T)$. The production losses represent the economic losses to the region because of the inoperability or lack of resilience in the utilities sector and ignores the different impacts caused by the hurricane on the other industries. If the budget is more than $100 million, the marginal decrease in production losses is less than the marginal increase in the budget, which suggests that spending a large amount of money (more than $100 million) on the utilities sector may not be cost effective. Since the expected production losses to the utilities sector is based on the resilience of the system, the plateau effect shown in Figure 3 also shows in Figure 4 when the budget exceeds approximately $150 million.

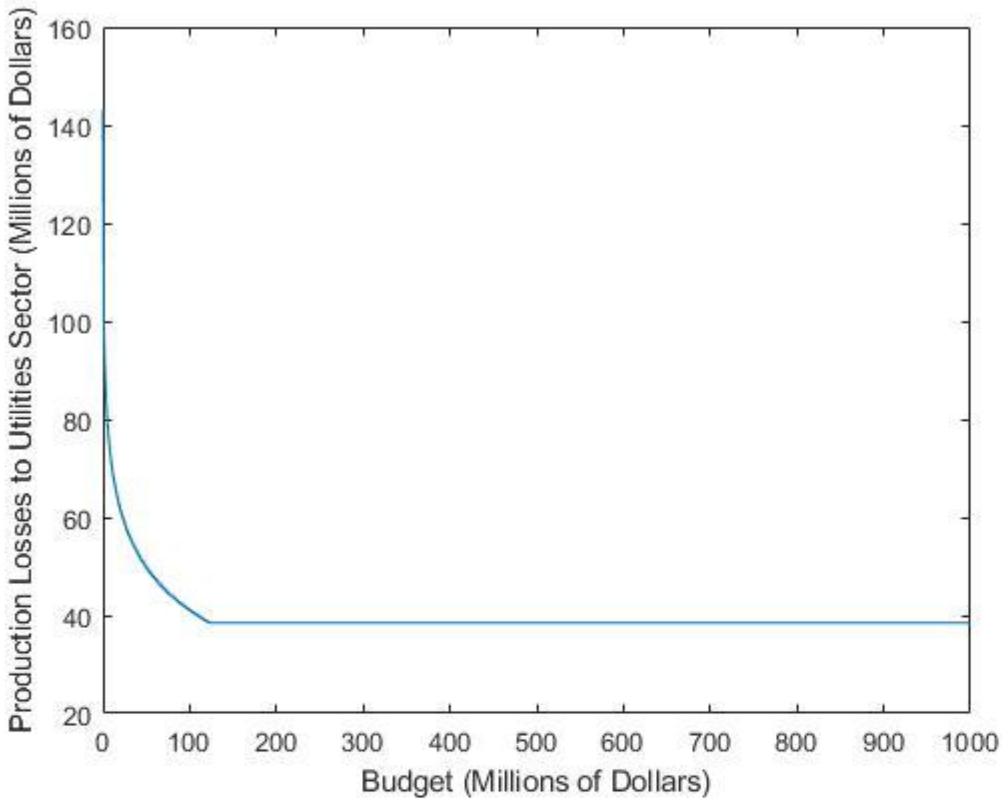

Figure 4: Expected Production Losses to Utilities Sector

3.4 Application of the American Red Cross

When a disruption occurs, countless numbers of organizations and individuals donate their time and resources to recovery. Some of these contributions can be difficult to quantify, which is something that is needed for the NGO model presented earlier. In order to see the impact that a NGO can have, the organization selected for this application is able to operate on a large scale throughout the entire impacted region and also has the resources to cause a significant effect on the working population. The American Red Cross was selected due to the historical data they provide on how many meals, relief items, and shelter stays they have distributed during similar disruptions as well as an estimated budget for their actions during those disruptions. During Hurricane Harvey, the Red Cross distributed millions of meals and relief items as well as assisting in the evacuation and rebuilding of the impacted region.

The input parameters for the NGO model are depicted in Table 7. They show the cost of allocating a single unit of food, relief item, and shelter stay both before and after the disruption as well as the weights associated with those variables. These per-unit cost values were determined by analyzing Red Cross reports to previous large disasters like Hurricane Harvey (American Red Cross, 2018). The weights for the variables was based on the importance of each variable relative to the other variables. The three weights sum to 0.9, which means that there is a 0.1 weight assigned to the product of the three value functions as depicted in Equation (5-3). This encourages the Red Cross to contribute to all three relief products (food, relief items, shelter).

Table 7: Input Values for Red Cross Model

	Pre-disruption food	Post-disruption food	Pre-disruption relief items	Post-disruption relief items	Post-disruption shelter stays
Cost	$1.33	$2.60	$1.87	$3.70	$40
Weight	0.6		0.2		0.1

Table 8 depicts the allocation of resources to food, relief items, and shelter for a budget ranging from $300 to $500 million. The results show that the total number of food and relief items distributed will continue to increase as the budget increases, but the number of shelter stays provided remains constant at 550,000. This behavior indicates that shelter stays might not be valued very highly due to their unit price, but the model incentivizes the Red Cross when providing at least some shelter stays. It is more valuable and cost effective to provide more food and relief items due to their higher weight when compared to shelter stays. If the cost of shelter stays were lower, the resources saved would likely go to providing more food and relief items rather than on more shelter stays. The fluctuation in values like pre-disruption food are likely due to the way the model is constructed. The model is run as a set of discrete points based on the desired budget, therefore the distribution of resources when the budget is $400 million has no effect on how the resources are distributed when the budget it $390 million or $410 million. It does, however, remain consistent that more resources are allocated to the post-disruption options than the pre-disruption options due to the low probability of the event occurring. If the disruption were more likely to occur, the model would reflect a larger emphasis on preparation.

Table 8: Optimal Red Cross Allocation (Millions of Units)

Budget	Pre-disruption food	Pre-disruption relief	Post-disruption food	Post-disruption relief	Post-disruption shelter stays
$300	16.52	5.76	43.92	33.75	0.55
$310	18.16	4.07	45.95	35.30	0.55
$320	18.81	11.11	45.38	34.88	0.55
$330	19.95	0.05	45.58	41.76	0.55
$340	21.32	0.71	47.18	43.37	0.55
$350	22.71	1.44	48.77	43.82	0.55
$360	23.14	2.58	48.43	46.14	0.55
$370	24.63	3.67	50.48	45.94	0.55
$380	26.26	4.80	52.87	45.99	0.55
$390	25.41	0.16	57.20	45.76	0.55
$400	28.98	7.12	56.75	46.42	0.55
$410	30.08	8.31	58.30	46.73	0.55
$420	31.17	9.52	59.99	47.29	0.55
$430	32.20	10.74	61.66	47.91	0.55
$440	33.09	11.99	63.14	48.44	0.55
$450	32.12	1.28	73.29	51.92	0.55
$460	34.85	14.53	66.39	49.77	0.55
$470	35.37	16.00	68.08	49.93	0.55
$480	35.64	10.92	75.05	52.67	0.55
$490	36.60	18.69	71.40	51.21	0.55
$500	37.22	20.09	73.06	51.84	0.55

Figure 5 depicts the expected production losses averted as a result of Red Cross spending. These production losses are a result of the workforce days saved being translated into an economic value for the region. The relationship between budget and production losses averted appears to be linear with approximately $18,500 averted per million dollars spent by the Red Cross. The value functions that were used in this model along with the linear conversion of food, relief items, and shelter stays makes it a little surprising that the relationship between budget and production losses averted is also linear. If the values of the weights and the minimum and maximum goals from the decision maker were adjusted, the relationship is expected to remain linear but with a higher slope as minimums are decreased. However, the purpose of placing weights and values on the three resource types is to ensure that the needs of the at-risk population are met so it is not advised that these values be reduced to zero. It should be expected that the industries that receive the most benefit from the Red Cross resource distributions are the industries with the largest working population.

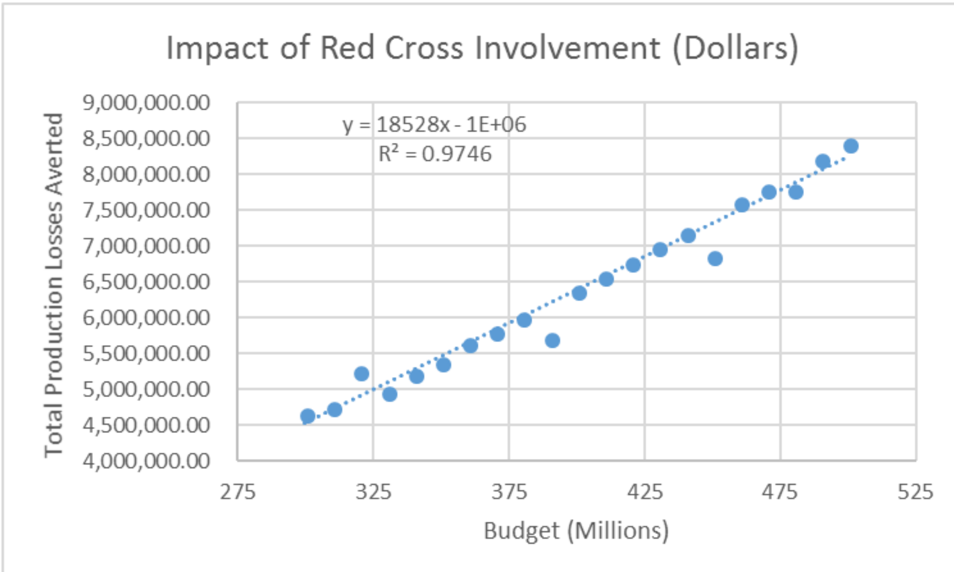

Figure 5: Expected Production Losses Averted Due to Red Cross

3.5 Shared Decision Making Among Decision Makers

For the federal government and state government models, there was an exponential relationship of decreasing marginal returns as the budget increased from zero. This resulted in the reduction of expected production losses by 80% in both cases as the budget reached its maximum point. Although this is a favorable result, government entities are usually focused on spending less rather than on spending more, and governments would like to achieve better results from the money they do spend. When private sector entities like a utilities company are able to spend their own resources to reduce the impact of a disruption, the economic production losses can also be reduced. If the contributions of NGOs can be quantified, even more production losses can be averted. By introducing the idea of shared decision making between all of the entities in a disruption environment, the same number of resources can be allocated more effectively and the overall impact to the entire region can be further reduced.

Up to this point, the decision makers in all four of the models are assumed to be making their decisions independent of each other. If the decision makers instead would share their decisions, the results of these models could be drastically different. Since the state government is more effective at assisting individual industries, it may be possible for the federal government to provide some of their response resources to the state government so that the federal government can focus on preparing for the disruptions. If the actions of the private sector are communicated to the entities that have wider scopes of influence like the state and federal government, less government money could be provided to that specific industry. This would help to reduce the amount of double spending and overspending that can occur when multiple entities are attempting to handle a disruption. If the impact that the NGOs will have is known to all decision makers, it is possible that their resources could be devoted to repairing the buildings and infrastructures themselves rather than spending on the working population.

This shared decision making can be quantified by calculating the effectiveness of all the decision makers on the regional level instead of at their respective levels, which has been done up to this point. This means that the impact of the state model, utilities model, and Red Cross model must be translated to the regional production level. By bringing all of the decision makers to the same level, the impact of the shared decision making can be expressed with $\mathbf{x}^T\mathbf{B}^{(n\times m)}\mathbf{c}^*$, where $\mathbf{c}^*$ is a vector of length m that represents the direct impacts after accounting for the resources allocated by each decision maker. The total impacts for industry i $c^*_{i,Reg}$ can be calculated with the following equation:

$$c^*_{i,Reg} = \hat{c}^*_{i,Reg} \exp\left(-k_q z_p - k_i z_i - k_{i,LAtoReg} z_{i,LA} - k_{i,PrivtoReg} z_{i,Priv} - k_{i,NGOtoReg} z_{NGO}\right) \quad (7)$$

where $k_{i,LAtoReg}$ represents the effectiveness of spending in Louisiana translated to a regional level, $z_{i,LA}$ is the state's spending for industry i, $k_{i,PrivtoReg}$ represents the effectiveness of private-sector spending translated to a regional level, $z_{i,Priv}$ is the private sector's spending for industry i, $k_{i,NGOtoReg}$ represents the effectiveness of the NGO spending translated to a regional level, and z_{NGO} is the spending by the NGO. When $\mathbf{x}^{\mathrm{T}}\mathbf{B}^{(\mathrm{n}\times\mathrm{m})}c^*_{i,Reg}$ is evaluated, it calculates the production losses for the entire region given the spending for each decision maker. Production losses from this shared decision making model should be less than the production losses from the federal government model alone.

Suppose that the total budget between the four decision making entities is $13 billion. Without shared decision making, this budget must be allocated within the economic limitations of the decision makers. For instance, it is impossible for the American Red Cross to be able to allocate a budget of $13 billion to a single disruption considering their total budget for the 2016 fiscal year was only about $2.7 billion (American Red Cross, 2016). If the federal government had a budget of $10 billion, the state government had a budget of $2.5 billion, the utilities company had a budget of $100 million, and the Red Cross had a budget of $400 million, the total production losses would be $20.35 billion. If the federal government spends $10 billion and no other entities allocate any money for preparedness or response, the production losses would be $27.08 billion. Including the effect of the other entities can significantly lessen the production losses. If the federal government realizes that total production losses could decrease if it provides money out of its budget to the other entities, this action could reduce the production losses even more. If the federal government's budget is just $7 billion, and the other $3 billion was distributed to the other entities, the state government's budget might be $5 billion, the utilities company's budget might be $500 million, and the Red Cross's budget might be $500 million. With this new budget allocation strategy brought about by the federal government providing more money to the state, the private sector, and NGOs, the production losses would be $19.96 billion. The difference between these two allocation strategies is only on the order of hundreds of millions of dollars, but having the federal government spend less in favor of more state and local spending can reduce production losses more. This result is due in large part to the state government being more effective in allocating money.

Therefore, by allowing the decision makers to communicate with one another, the resulting savings could justify the time it would take for the decision makers to work together and further illustrate the importance of communication during disruptions. This effect could be further increased if the other four state governments, other large private entities, or other large NGOs like Habitat for Humanity were included in the decision environment. Based on the results of the models, it is true that if the entire $13 billion budget was allotted to the federal government the production losses could be less than the $20.35 billion of the shared decision making model due to the larger effect that the federal government can have on the entire five state region. However, this is not a realistic application because it is very unlikely that all of the decision makers could be convinced to give all of their resources to a single entity. Each of the decision makers has their own set of expectations that they want to achieve and would not allow all of their resources to be taken before they can achieve at least some of those expectations.

As mentioned previously, the Red Cross's goal is not economic recovery. Red Cross efforts during a disruption such as a hurricane often focus on those people who are most devastated by the event. These people need the basic necessities such as food, clothing, and shelter to survive. Often, the people who need these basic necessities after a disruption are the most vulnerable or at-risk populations before the disruption occurs. The most vulnerable populations may be the elderly or the socio-economically disadvantaged such as those living below the poverty line and those that did not have a home before the disruption. Neglecting the at-risk population can increase the number of injured that go unaided or even increase the number of casualties as a result of the disruption. With a limited budget, decision makers may need to determine how to fairly divide a budget for economic recovery and to assist the most vulnerable populations. The resource allocation model can be used to understand this possible trade-off between helping the most vulnerable and economic recovery.

Assume there is only $1 billion available for the federal government and the American Red Cross to share. The federal government spends money to help the regional economy recover and the Red Cross spends money to provide food, shelter, and relief items to the most vulnerable populations. Figure 6 displays the relationship between the production losses due to the federal government's spending and the person-days helped by the Red Cross. The far right portion of the curve illustrates when the Red Cross receives the entire $1 billion budget while the far left point of the curve illustrates when the federal government receives the entire $1 billion budget. There is a slight logarithmic curve to the data which indicates that there may be a point where the largest mutual benefit could be selected. This point balances the trade-off between helping the economy and helping the at-risk population.

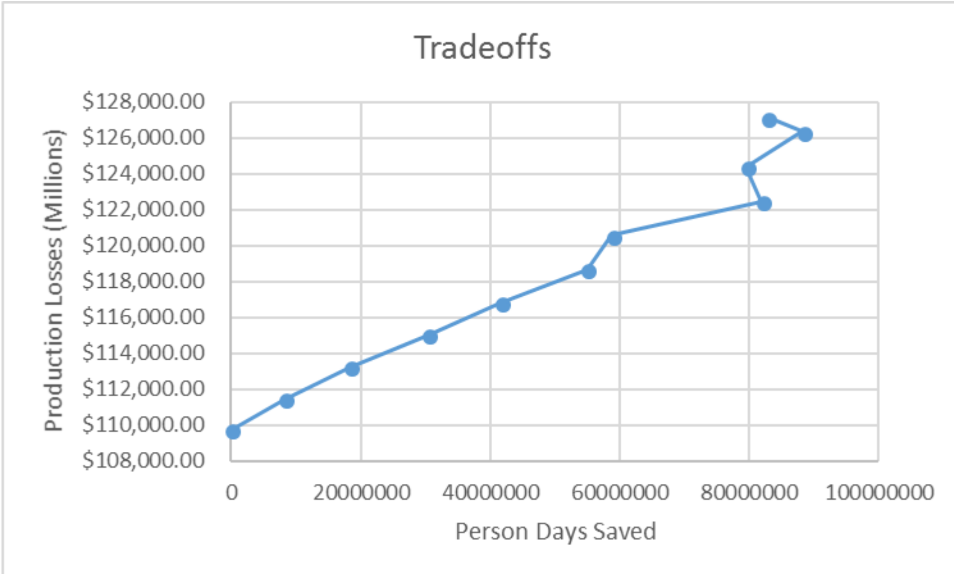

Figure 6: Tradeoff Between Person Days and Production Losses

Chapter 4. Conclusions and Insights

Major disruptions are events that cannot always be prevented even with an unlimited budget. It is important that proper resource allocations plans are in place before those disruptions occur. The preparation for those disruptions can reduce the consequences of the disruption and help to reduce the amount of resources need to respond to and recover from those disasters. This thesis approached a resource allocation problem from the perspective of four independent decision makers, each with different objectives and resources. Each decision maker could also operate with different effectiveness. Those four different perspectives were illustrated by four computational models that provided results in terms of production losses in an economic region. The models developed here were applied to a disruption on the scale of Hurricane Katrina in the context of the 2015 U.S. Gulf Coast economy. Combining the results of the four different decision-making models into a single metric of production losses enables us to analyze the effect of shared decision making among the four decision makers. By allowing the federal government to redistribute some of its budget to the other decision makers via shared decision making, production losses could be reduced by hundreds of millions of dollars with the same overall budget. The unique contributions of this thesis are modeling four decision makers with different objectives and resources, including the distinct decision makers each with their own decision problem, converting the output from each decision model into a single computational measure that is shared by all the models, and analyzing how collaborating among the decision makers can improve the overall result of a resource allocation problem.

There are many applications for each of the models discussed. Each of the models can be used by a decision maker to run any number of “what if” situations based on their own data for events that have already happened to see where they could have been more effective. The models can also be used as predictive models for events that a decision maker feels could happen in the near future to anticipate losses and devise ways to reduce those anticipated losses. The shared decision-making model can be used to illustrate the importance of communication in disruption situations to make the most effective use of the finite resources that each decision maker has available.

Some of the values used in the creation of these models to establish parameters and quantify loss are based on the best estimates that could be obtained from other research papers and information accessible on the entities. A future step for this research is the further validation of the input parameters used in order to provide the most accurate model possible. The relationship between smaller decision makers and the entire decision environment to better illustrate the connections between industries can also be done. The model can be modified and applied to any number of potential disruptions and should be fit to multiple decision maker archetypes.

References

Alp Ertem, Mustafa, and Nebil Buyurgan. "An auction-based framework for resource allocation in disaster relief." *Journal of Humanitarian Logistics and Supply Chain Management* 1.2 (2011): 170-188.

Altay, N. and Green III, W. G. 2006. OR/MS research in disaster operations research. *European Journal of Operational Research, 175*, 475-493.

American Red Cross. "2016 Annual Report." *American Red Cross 2016 Annual Report*, 2016, www.redcross.org/images/MEDIA_CustomProductCatalog/m64340273_Annual-Report-2016.pdf.

American Red Cross. "Hurricane Harvey 6 Month Update." *Hurricane Harvey Relief Information*, Mar. 2018, embed.widencdn.net/pdf/plus/americanredcross/ivbxdlqyyc/hurricane-harvey-6-month-update.pdf?u=hugfg1&proxy=true.

Barbarosoğlu, G., and Arda, Y. (2004). A two-stage stochastic programming framework for transportation planning in disaster response. *Journal of the operational research society*, *55*(1), 43-53.

Barry, Bruce, and Greg L. Stewart. "Composition, process, and performance in self-managed groups: The role of personality." *Journal of Applied psychology* 82.1 (1997): 62.

Beven, J. L., Avila, L. A., Blake, E. S., Brown, D. P., Franklin, J. L., Knabb, R. D., Pasch, R. J., Rhome, J. R. and Stewart, S. R. 2008. Atlantic hurricane season of 2005. *Monthly Weather Review*, 136, 1109-1173.

Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, Shinozuka M, Tierney K,Wallace W, vonWinterfeldt D. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 2003; 19(4):733–752.

Brunkard, J., Namulanda, G. and Ratard, R. 2008. Hurricane katrina deaths, Louisiana, 2005. *Disaster medicine and public health preparednes*s, 2, 215-223.

Burton, Mark L., and Michael J. Hicks. "Hurricane Katrina: preliminary estimates of commercial and public sector damages." *Marshall University: Center for Business and Economic Research* (2005).

Carter, W. Nick. 2008. *Disaster Management: A Disaster Manager's Handbook*. © Asian Development Bank. http://hdl.handle.net/11540/5035. License: CC BY 3.0 IGO.

Caunhye, Aakil M., Xiaofeng Nie, and Shaligram Pokharel. "Optimization models in emergency logistics: A literature review." *Socio-economic planning sciences* 46.1 (2012): 4-13.

Chi, J., VanLeeuwen, J. A., Weersink, A., and Keefe, G. P. (2002). Direct production losses and treatment costs from bovine viral diarrhea virus, bovine leukosis virus, Mycobacterium avium subspecies paratuberculosis, and Neospora caninum. *Preventive veterinary medicine*, *55*(2), 137-153.

Chittaro, Luca, and Riccardo Sioni. "Serious games for emergency preparedness: Evaluation of an interactive vs. a non-interactive simulation of a terror attack." *Computers in Human Behavior* 50 (2015): 508-519.

Clemen, R. T. and Reilly, T., *Making Hard Decisions with Decision Tools*: South-Western Cengage Learning, 2001.

Coles, John, and Jun Zhuang. "Decisions in disaster recovery operations: a game theoretic perspective on organization cooperation." *Journal of Homeland Security and Emergency Management* 8.1 (2011).

Comfort, Louise K., Kilkon Ko, and Adam Zagorecki. "Coordination in rapidly evolving disaster response systems: the role of information." *American Behavioral Scientist* 48.3 (2004): 295-313.

Crowther, K. G., Haimes, Y. Y. and Taub, G. 2007. Systemic valuation of strategic preparedness through application of the inoperability input-output model with lessons learned from Hurricane Katrina. *Risk Analysis*, 27, 1345-1364.

De la Fuente, Alejandro. "Government expenditures in pre-and post-disaster risk management." *Background note for World Bank* (2010).
Dubrovsky, Vitaly J., Sara Kiesler, and Beheruz N. Sethna. "The equalization phenomenon: Status effects in computer-mediated and face-to-face decision-making groups." *Human-computer interaction* 6.2 (1991): 119-146.
Economics And Statistics Administration 2005. Hurricane Katrina: Economic Impacts 3-1/2 Months after Landfall. In: COMMERCE, D. O. (ed.).
Farazmand, Ali, ed. *Handbook of crisis and emergency management*. CRC Press, 2001.
Fiedrich, Frank, Fritz Gehbauer, and Uwe Rickers. "Optimized resource allocation for emergency response after earthquake disasters." *Safety science* 35.1-3 (2000): 41-57.
Garrett, T. A. and Sobel, R. S. 2003. The political economy of FEMA disaster payments. Economic Inquiry, 41, 496-509.
Geldermann, Jutta, et al. "Multi-criteria decision support and evaluation of strategies for nuclear remediation management." *Omega* 37.1 (2009): 238-251.
Golany, Boaz, et al. "Nature plays with dice–terrorists do not: Allocating resources to counter strategic versus probabilistic risks." *European Journal of Operational Research* 192.1 (2009): 198-208.
Godschalk, D. R., Rose, A. Z., Mittler, E., Porter, K. and West, C. T. 2009. Estimating the value of foresight: aggregate analysis of natural hazard mitigation benefits and costs. Journal of Environmental Planning and Management, 52, 739-756.
Guitouni, A., and Martel, J. M. (1998). Tentative guidelines to help choosing an appropriate MCDA method. *European Journal of Operational Research*, *109*(2), 501-521.
Haimes, Y. Y. 1998. Risk Modeling, Assessment, and Management. Wiley and Interscience, New York, New York.
Hallegatte, S. E. P. 2008. An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina. *Risk Analysis*, 28**,** 779-799.
Hallegatte, S. E. P. 2011. Modeling the Role of Inventories in the Assessment of Natural Disaster Economic Costs: Application on Hurricane Katrina in Louisiana. *Submitted to Risk Analysis.*
Heath, Robert. "The Kobe earthquake: Some realities of strategic management of crises and disasters." *Disaster Prevention and Management: An International Journal* 4.5 (1995): 11-24.
Healy, A. and Malhotra, N. 2009. Myopic voters and natural disaster policy. *American Political Science Review*, 103**,** 387-406.
Hick, John L., Dan Hanfling, and Stephen V. Cantrill. "Allocating scarce resources in disasters: emergency department principles." *Annals of emergency medicine* 59.3 (2012): 177-187.
Holtz-Eakin, D. 2005. Macroeconomic and budgetary effects of Hurricanes Katrina and Rita. *U.S. House Committee on the Budget*. Washington, D.c.: Congressional Budget Office
Hurricane Research Division. 2015. *Continental United States Hurricane Impacts/Landfalls, 1851-2015* [Online]. Atlantic Oceanographic & Meteorological Laboratory. National Oceanic & Atmospheric Administration. [Accessed February 14 2017].
Joumard, Isabelle, and Claude Giorno. "Enhancing the effectiveness of public spending in Switzerland." (2002).
Kaplan, Stanley, and B. John Garrick. "On the quantitative definition of risk." *Risk analysis* 1.1 (1981): 11-27.
Keeney, R.L. and Raiffa, H., *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. New York: John Wiley & Sons, 1976.
Keeney, R. L., *Value-Focused Thinking: A Path to Creative Decisionmaking*. Cambridge, MA: Harvard University Press, 1996.

Levy, Jason K., et al. "Multi-criteria decision support systems for flood hazard mitigation and emergency response in urban watersheds." *JAWRA Journal of the American Water Resources Association* 43.2 (2007): 346-358.

Levy, Jason K., and Kouichi Taji. "Group decision support for hazards planning and emergency management: A Group Analytic Network Process (GANP) approach." *Mathematical and Computer Modelling* 46.7-8 (2007): 906-917.

LSU Division Of Economic Development 2011. The 2011 Louisian Tourism Satellite Account: An Update.

MacKenzie, C. and Al-Kazimi, A. 2017. Optimal Resource Allocation to Prevent, Prepare, and Respond to Multiple Disruptions. *Iowa State University.*

Mackenzie, C. A., Baroud, H. and Barker, K. Optimal resource allocation for recovery of interdependent systems: Case study of the Deepwater Horizon oil spill. IIE Annual Conference. Proceedings, 2012b. Institute of Industrial Engineers-Publisher, 1.

Mackenzie, C. A., Baroud, H. and Barker, K. 2016. Static and dynamic resource allocation models for recovery of interdependent systems: Application to the *Deepwater Horizon* oil spill. *Annals of Operations Research,* 236**,** 103-129.

MacKenzie, Cameron A., and Christopher W. Zobel. "Allocating resources to enhance resilience, with application to Superstorm Sandy and an electric utility." *Risk Analysis* 36.4 (2016): 847-862.

McEntire, D.A. (2004), "*The status of emergency management theory: issues, barriers, and recommendations for improved scholarship*", *Conference Proceedings of the Federal Emergency Management Agency (FEMA) Higher Education Conference June 8, 2004, Emmitsburg, MD*.

Norris, Fran H., et al. "Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness." *American journal of community psychology* 41.1-2 (2008): 127-150.

Oerke, E. C., and Dehne, H. W. (2004). Safeguarding production—losses in major crops and the role of crop protection. *Crop protection*, *23*(4), 275-285.

Orsi, Mark J., and Joost R. Santos. "Probabilistic modeling of workforce-based disruptions and input–output analysis of interdependent ripple effects." *Economic Systems Research* 22.1 (2010): 3-18.

Oxford Economics 2010. Potential Impact of the Gulf Oil Spill on Tourism. U.S. Travel Association.

Papadakis, Ioannis S., and William T. Ziemba. "Derivative effects of the 1999 earthquake in Taiwan to US personal computer manufacturers." *Mitigation and Financing of Seismic Risks: Turkish and International Perspectives*. Springer, Dordrecht, 2001. 261-276.

Ritchie, Brent W. "Chaos, crises and disasters: a strategic approach to crisis management in the tourism industry." *Tourism management* 25.6 (2004): 669-683.

Rose, A., Porter, K., Dash, N., Bouabid, J., Huyck, C., Whitehead, J., Shaw, D., Eguchi, R., Taylor, C. and Mclane, T. 2007. Benefit-cost analysis of FEMA hazard mitigation grants. Natural hazards review, 8, 97-111.

Saaty, Thomas L. "Analytic Hierarchy Process." *Wiley StatsRef: Statistics Reference Online* (1980).

Santos, J. R. 2006. Inoperability Input-Output Modeling of Disruptions to Interdependent Economic Systems. *Systems Engineering,* 9**,** 20-34.

Santos, J. R. and Haimes, Y. Y. 2004. Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. *Risk Analysis,* 24**,** 1437-1451.

Setola, Roberto, and Stefano De Porcellinis. "A methodology to estimate input-output inoperability model parameters." *International Workshop on Critical Information Infrastructures Security*. Springer, Berlin, Heidelberg, 2007.

Shan, Xiaojun, and Jun Zhuang. "Hybrid defensive resource allocations in the face of partially strategic attackers in a sequential defender–attacker game." *European Journal of Operational Research* 228.1 (2013): 262-272.

Sherali, H. D., Carter, T. B., and Hobeika, A. G. (1991). A location-allocation model and algorithm for evacuation planning under hurricane/flood conditions. *Transportation Research Part B: Methodological*, *25*(6), 439-452.

Sheu, Jiuh-Biing, Yen-Heng Chen, and Lawrence W. Lan. "A novel model for quick response to disaster relief distribution." *Proceedings of the Eastern Asia Society for Transportation Studies*. Vol. 5. No. 1. 2005.

Smith, Wally, and John Dowell. "A case study of co-ordinative decision-making in disaster management." *Ergonomics* 43.8 (2000): 1153-1166.

U.S. Census Bureau. "Mississippi; Alabama; Florida; Texas; Louisiana; UNITED STATES." *QuickFacts Table*, www.census.gov/quickfacts/fact/table/MS,AL,FL,TX,LA,US/PST045216.

U.S. Department of Commerce. Bureau of Economic Analysis 2015. Full and Part-Time Employment by State and Metropolitan Area.

U.S. Department of Commerce. Bureau of Economic Analysis 2015. Gross Domestic Product (GDP) by State and Metropolitan Area.

U.S. Department of Commerce. Bureau of Economic Analysis 2015. Local Area Personal Income (LAPI) by State and Metropolitan Area.

Yu, Lean, and Kin Keung Lai. "A distance-based group decision-making methodology for multi-person multi-criteria emergency decision support." *Decision Support Systems* 51.2 (2011): 307-315.

Zobel CW, Khansa LZ. Quantifying cyber infrastructure resilience against multi-event attacks. *Decision Sciences*, 2012; 43(4):687–710.