INFRASTRUCTURE RESILIENCE AT THE PROJECT LEVEL: CONSIDERING HAZARD RISK AND UNCERTAINTY FOR INFRASTRUCTURE DECISIONS

by

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ABSTRACT

Disasters, such as Hurricane Sandy, the Japan Tōhoku Tsunami and others, illustrate the effects of infrastructure system failure on communities. Although the idea of increasing resilience is becoming a popular response to these challenges, it can be difficult to determine exactly how to make infrastructure systems more resilient.

This thesis proposes an approach that may be used to inform decisions that strengthen infrastructure resilience. Decisions for resilience should be made by first setting performance requirements for proxy measures of resilience, such as life cycle cost, risk, time to recovery and reliability. Analysis can then be performed to determine how different decisions may meet those performance requirements even in the presence of uncertainty. Life cycle cost analysis, risk assessment and other tools can be used within this approach to model the performance of the system. Other tools such as bounding and information gap theory can be used to model the uncertainties involved in the problem. This analysis approach should be applied iteratively to better inform decisions for infrastructure resilience.

This approach can be used to determine how much to spend on resilience, what alternatives should be pursued, and what events infrastructure should be designed for. The approach allows decision makers to pursue resilience according to their own values and allows for analysis even with great uncertainty. Although this approach provides a guide to follow, there can arise many challenges in making decisions for resilient infrastructure. These challenges arise from the uncertainty and complexity involved in the interactions amongst hazards, infrastructure and society.

Chapter 1

INTRODUCTION

1.1 Motivation

Modern society heavily relies on infrastructure systems to support quality of life, economic development, life safety and nearly every aspect of everyday living. Because of this reliance, infrastructure system failures due to extreme events or disasters can have enormous impacts on people. These impacts vary in severity, ranging from traffic delays and dropped calls to total property destruction and death. In the wake of a disaster, the extent and duration of infrastructure disruptions has a major impact in how severely people are affected and how quickly they recover. The impact of infrastructure disruptions is evident in recent disasters.

After Hurricane Sandy in 2012, the broadest impacts were due to infrastructure service disruptions. More than 8 million power outages were experienced across 17 states (Kaufman et al. 2012). In New York City alone, power outages affected 70,000 businesses while highway, rail and transit disruptions frustrated more than 11 million travelers. The failure of infrastructure and the time required to recover from failures were key factors in the storm's impacts to business, people and the community as a whole. Most of the 70,000 businesses without power couldn't do business. People had difficulty getting back to work until gasoline supply and transit service were restored throughout the city. These impacts further propagated through other sectors. Power outages and other utility failures was a major cause for evacuation among the six hospitals and 31 nursing homes evacuated due to Hurricane Sandy (PlaNYC 2013).

Beyond influencing disaster impacts, infrastructure failure is also capable of amplifying disaster, or even creating disaster on its own. After Hurricane Katrina in 2005 the failure of hurricane protection infrastructure in New Orleans greatly increased the damage brought by the storm. The flood protection infrastructure in place in New Orleans failed to perform its function, causing a number of casualties as well as the complete destruction of many homes and businesses (Andersen 2007).

After the 2011 Tohuku Japan earthquake and tsunami, failures at the Fukushima nuclear generating station caused a loss of containment event leading to radiation releases. This created a new radiation disaster whose impacts only further complicated the response and recovery from the already devastating impacts of the earthquake and tsunami (Fukushima Nuclear Accident Independent Investigation Commission 2012).

Other incidents demonstrate that infrastructure failure can cause disaster on its own even without an extreme event. In 2003, a blackout across the Northeastern United States left 50 million people without electricity. The blackout was not triggered by any extreme event, it occurred on a completely normal day due to network design and operating errors. It not only disrupted power service but also interrupted mass transit, liquid fuel supply and water infrastructure. The event cost the public between 4 and 10 billion dollars and was a contributing factor in a number of deaths and injuries due to car accidents, fires from candles and carbon monoxide inhalation from generators. (Anderson et al. 2007). Similarly, the I-35W bridge collapse, which also occurred on an typical day, killed 13 and caused traffic delays for months (NTSB 2008). These events illustrate that infrastructure failure can be very dangerous, creating new disasters even without extreme environmental loading.

1.2 Resilience

In an effort to reduce the negative impacts of disaster, nations, communities and organizations are becoming more interested in the concept of disaster resilience. Resilience is essentially the ability to prepare for, resist, absorb, adapt to and recover from adverse events. Resilience can be applied both for communities as a whole, as well as for infrastructure in particular. While the research community continues to debate the definition and measurement of resilience, policy makers and practitioners at various levels are already beginning to adopt resilience as a strategy to strengthen communities against disaster.

1.2.1 What is Resilience?

Many definitions have been given to resilience in general and a number exist for infrastructure resilience in particular. The concept of resilience stems from the fields of materials science and ecology. Resilience in materials science refers to the ability of a material to return to its original size and shape after deformation. In ecology resilience refers to the "persistence of systems and their ability to absorb change and disturbance and still maintain the same relationships between … state variables" (Holling 1973).

Most definitions describe resilience as an ability or capacity of systems in the face of disruption. It has been described as an ability or capacity to withstand, retain function, cope, adapt, absorb and recover (National Research Council 2012; Madni and Jackson 2009; Haimes 2009). Some have advocated that resilient design addresses unknown, unexpected hazards; while traditional risk-based methods only consider known risks (Park et al. 2011; Haimes 2009).

There are many different perspectives on the concept of resilience and these perspectives are influential in how resilience is defined. From a whole community disaster resilience perspective an important definition comes from the National Academies report which defines resilience as, "*the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events* (National Research Council 2012)*."* A systems engineering perspective comes from INCOSE (the International Council on Systems Engineering) which defines it as "the ability of organizational, hardware and software systems to mitigate the severity and likelihood of failures or losses, to adapt to changing conditions, and to respond appropriately after the fact" (Jackson and Ferris 2012). While many definitions and metrics exist, this thesis will focus on achieving resilience using the National Academies and INCOSE definitions. Chapter 2 further addresses how this thesis will approach resilience.

1.2.2 Resilience in Policy and Practice

Although researchers are still debating resilience, it is already becoming an important guiding principle for public policy and planning. Internationally, the 2005 United Nations *Hyogo Framework for Action* was created for "building resilience of nations and communities to disasters (UNISDR 2005)." At a national level, the 2011 *Whole Communities* initiative outlines principles for communities to become more resilient (FEMA 2011). The 2009 U.S. National Infrastructure Protection Plan and National Infrastructure Advisory Council Critical Infrastructure Resilience report detail the specific need for resilient infrastructure (Bush et al. 2009; Chertoff 2009). Resilience is highlighted at the state level in the Oregon Resilience Plan which focuses on seismic hazards and the New York State 2100 Plan which was developed in response to Hurricane Sandy (Rodin et al. 2013; Yu et al. 2013). At the local level documents such as Boston Harbor Association's *Rising Tide* report and New York City's *Building a Stronger More Resilient New York* describe the need for resilient infrastructure to face sea level rise and flooding risks (Douglas et al. 2013; PlaNYC 2013). These documents and others promote resilient infrastructure as a way to mitigate the impact of extreme events.

1.3 Problem Statement

Although resilience makes for an excellent guiding concept to reduce disaster impacts, the planning, design, maintenance, operations and management of resilient infrastructure is not straightforward. Even with proper motivation and funding, there are numerous challenges in actually making infrastructure more resilient in a cost effective manner. The complexity of the systems, finite resources and uncertainties involved in making decisions for resilient infrastructure, make it a difficult task.

The behavior of and interactions between hazards, infrastructure and the community can be very complex and hard to model. In many cases there are many unknowns about the hazard itself. For many hazards, information remains sparse. For hazards like terrorism, and nuclear accidents, fortunately, experience is limited, leaving many unknowns. For others, like earthquake and climate change hazards, past experience may not be useful for inferring future hazard risk. Relationships between hazards and infrastructure impacts are often non-linear and complex, involving many failure modes throughout the infrastructure system. The impacts of infrastructure disruptions on the community are likewise difficult to understand. These complexities make choosing a resilient alternative difficult.

Since there are countless opportunities to improve resilience and only finite resources to do so, the challenge is to balance the benefits of resilience against the costs required to implement it. This can be very difficult, as the benefit of resilience is often not easily quantifiable. Even when the benefits are quantifiable, the calculation of benefits is only possible by making assumptions about the nature of the system.

Underlying all of this is uncertainty. Uncertainty is what we do not know. Resilience not only considers well known, well understood hazards, but also poorly understood and unexpected hazards. There is no data about unexpected hazards; even for real hazards there is very limited data for extreme events. How can New York plan be resilient against a category 3 hurricane, when it has never experienced one? Even known hazards have an element of uncertainty. Even if the probability of a flood event is known, nobody actually knows whether or not it will happen. Furthermore, in many cases although there are estimates on hazard probability, these estimates are often shrouded in uncertainty. Uncertainties propagate through the entire process. An uncertain model of hazard behavior may be used to predict infrastructure performance, adding more uncertainty. As the predicted infrastructure performance is used to calculate the effect on the community, further uncertainties are introduced. Uncertainty creeps into the problem in every model, every number, and every equation used to model infrastructure disaster resilience.

Making decisions to increase infrastructure resilience can be challenging. These decisions are fraught with the complexities of hazards, communities and infrastructure. Making decisions that improve infrastructure resilience is difficult because resilience cannot be quantified, disaster impacts cannot always be monetized, and uncertainty obscures every element in the equation.

1.4 Scope

Fundamentally, improving infrastructure resilience seeks to address infrastructure risk. However, infrastructure risk is a very broad topic. There are many ways to divide the field. Infrastructure risk may be divided by sector, scale, and risk type.

Infrastructure can be divided up by sector; common sector divisions include transportation, energy, water, wastewater, communications and others. These sectors may be further subdivided. For example, transportation can be subdivided into highway, rail, water and transit. Likewise the energy sector could be divided into electrical power, natural gas and liquid fuels. Although these sectors are very different, exposure to infrastructure risk is similar amongst sectors.

Infrastructure can also be examined at different scales. At the community scale, infrastructure risk comprises the many interdependencies amongst sectors and their relationship with the community as a whole. At a system or network level, infrastructure operators are concerned with how different pieces of their system work together and interact to produce consistent service. At the infrastructure element or project level, operators are concerned with a single piece of infrastructure such as a road or pipe segment, bridge, pump station or substation.

Infrastructure risk may also be categorized by the type of risk faced. There are a host of risks that infrastructure faces. Infrastructure projects face technical, management, economic, political and failure risks Technical risks may stem from unproven technology and changes in technology or standards. Management risks consist of poor allocation of time or resources, inconsistent objectives, resource conflicts and inadequate expertise. Infrastructure operators can be exposed to economic risks due to fluctuations in demand for service and fluctuations in material, energy and labor costs. Political risk may stem from difficult to complete regulations, future regulations and the changing of funding and goodwill that may occur as public opinion and elected officials change. Infrastructure failure risks are caused by accidents, deterioration, terrorism and natural hazards. Accidents may include engineering or construction mistakes and unforeseen operator error, equipment explosions and vehicle or vessel impacts to critical elements. Natural hazards include severe storms, tornadoes, hurricanes, tsunami, earthquakes and mass movement (Ayyub and McCuen 2011). Infrastructure faces a very diverse set of risks.

The scope of this thesis can be defined in terms of infrastructure sector, risk type and functional scale. This thesis attempts to develop principles useful to most infrastructure sectors but leans more towards transportation. As for risk types, this thesis focuses on failure risks, with an emphasis on natural hazards and in particular flooding risks due to severe storms, hurricanes and sea level rise. This thesis focuses on making decisions at the infrastructure element or project scale, although these decisions are influenced by considering a given piece of infrastructure's context at the network and community scale.

1.5 Objectives

The objective of this work is to develop an approach for infrastructure decision makers to make better decisions about infrastructure resilience under uncertainty. The approach has the following objectives:

- Be applicable to multiple sectors and varied infrastructure risks
- Explicitly and quantitatively consider risk when needed and possible
- Be useful even in the presence of a high degree of uncertainty
- Allow the decision maker to evaluate multiple criteria

- Be quantitative when it can, qualitative when it must
- Be as simple as possible, but scalable to larger problems

1.6 Overview of the Thesis

This thesis first discusses attributes and metrics that can be used to measure resilience. Next, existing techniques for infrastructure decision making are discussed in chapter three. The challenges that uncertainty presents these analysis methods are discussed in chapter four. Chapter five outlines an approach to combine existing analytical tools and uncertainty tools to address resilience problems. In chapters six and seven this approach is applied in two case studies. The last chapter concludes with a discussion of possible applications, limitations, challenges and future work.

Chapter 2

RESILIENCE ATTRIBUTES AND METRICS

It is useful to break up resilience into its key outcomes to make decisions to enhance infrastructure resilience. These outcomes are defined in one of the more influential research papers on resilience as follows(Bruneau et al. 2003):

1. Reduced failure probabilities
2. Reduced consequences from failures
3. Reduced time to recovery

These outcomes are useful to help decision makers evaluate the extent to which their decisions further resilience. This chapter will discuss various attributes and metrics that can be used to consider how a system may achieve resilience outcomes.

2.1 Attributes of Resilient Systems

There are many system attributes that contribute to resilience. Although others have chosen to organize attributes in various ways (Madni and Jackson 2009; Bruneau et al. 2003; Jackson 2010; Hollnagel et al. 2006), here these attributes are organized according to the resilience outcome that they best support. Grouped by resilience outcomes, attributes are separated into those that reduce failure probability, those that reduce failure consequences and those that reduce the time to recovery.

2.1.1 Reduce Failure Probability

A number of system attributes are useful for reducing the probability of a failure event. These attributes are often associated with the physical nature of the system itself. These attributes all tend to describe some element of a system's capacity to withstand an adverse event without a total loss of performance. The following system attributes work to achieve the outcome of reduced failure probability.

- **Robustness**: The ability of system elements to withstand some demand without performance degradation or failure (Bruneau et al. 2003).
- **Absorption**: The ability of a system to absorb an adverse event. For example, dunes absorb energy from a hurricane before it reaches a community (Woods 2006).
- **Redundancy**: System elements or subsystems are substitutable, in that there are alternative means to meet functional requirements (Madni and Jackson 2009; Bruneau et al. 2003).
- **Margin**: Adequate safety factors are used to provide for performance beyond expected design loads even with uncertainties in system elements (Jackson 2010).
- **Context-spanning**: The system is designed both for worst case and most likely event scenarios (Jackson 2010).
- **Loose Coupling**: The system is built such that failures in one area don't easily propagate to others (Jackson and Ferris 2012; Perrow 1984).

2.1.2 Reduce Failure Consequences

The reduction of failure consequences is achieved as physical systems fail in ways such that consequences are limited and operators have the ability to somehow lessen the effects of a disruption. The following attributes serve to reduce the consequences of a failure:

- **Graceful Degradation**: System performance degrades gradually after a disruption (Jackson and Ferris 2012).
- **Localized Capacity**: The functionality of the system is distributed across various nodes, such that when one node fails, others continue to provide service (Jackson and Ferris 2012).
- **Predictability**: System operators are able to predict disruptions and are prepared to respond (Jackson 2010).
- **Human Back-up**: When automatic systems fail, humans have the opportunity to intervene to correct problems (Madni and Jackson 2009).
- **Human in the Loop**: Humans are continuously in control of the system and can observe and respond to adverse events (Madni and Jackson 2009).

2.1.3 Reduce the Time to Recovery

Attributes that primarily achieve the end of reducing the time to recovery are generally concerned with the ability of the organizations to intervene after a disruption to restore service to acceptable levels. The following attributes help speed up the time to recovery:

- **Reorganization**: Teams can quickly re-organize themselves to accomplish the tasks necessary to recover (Jackson 2010).
- **Inspectability**: After an event, the system can be easily inspected for damage (Jackson 2010).
- **Repairability**: System elements can be easily repaired when damaged (Jackson and Ferris 2012).

The numerous and diverse attributes above illustrate the many qualities of a system that can influence its resilience. In many cases these qualities cannot be easily measured individually, nor can these qualities be easily combined to measure overall resilience. While these attributes should certainly be kept in mind in infrastructure design and management decisions, it can be very difficult to know how to apply them. For example, in designing a system engineers may have to make tradeoffs, deciding whether to reduce failure probability by using greater margins or by introducing more redundancy. While these principles all generally improve resilience it is difficult to know which should be used and when.

2.2 Resilience Metrics

The application of resilience attributes can be partially aided by the use of metrics. Although these metrics cannot describe exactly how the application of resilience principles contributes to resilience, they can be used to give decision makers a little more information about the effect of various decisions on overall resilience. While resilience itself is not easily measured, a number of correlated metrics can be used to provide some insight into resilience. A variety of cost and performance metrics can be used to guide more resilient decisions.

2.2.1 Costs

Although implementing resilience may incur a higher initial cost, over the long term it is hoped that resilience will lead to lower costs thanks to fewer failures, less consequences of failure, and faster recoveries. Cost is an important metric for resilience. It can be used both to measure the cost to build resilience and the benefits of reduced failures and subsequent consequences. There are many different types of costs that may be considered and a variety of ways of categorizing these costs. Cost metrics may be categorized by the party paying the cost:

- Agency Costs: Costs to the agency which is responsible for the infrastructure in question (e.g. a state department of transportation).
- User Costs: Costs to the users of the infrastructure (e.g. highway users).
- Non-User Costs: Costs to the surrounding community (e.g. businesses off of the highway)

Costs may also be categorized by when they are incurred:

- Initial Costs: Costs incurred in the near term during construction or retrofit to improve disaster resilience (FHWA 2002).
- Maintenance & Operations Cost: Costs are distributed across the life cycle of the infrastructure (FHWA 2002).
- Failure Costs: Costs incurred when an adverse event occurs, infrastructure fails and a disruption is created. Since the analyst will not know when or if this will happen, these costs are generally assumed to be incurred over the course of the entire lifecycle of the infrastructure, even though in reality they occur at one discrete moment in time (Wen 2001; Chang and Shinozuka 1996).
- End of life costs: The value of an asset at the end of its useful life or the cost required for disposal (FHWA 2002).

These costs can be aggregated to calculate the life cycle cost of the infrastructure, which is the total cost of the infrastructure over its lifetime. Costs are an important metric because in many cases when organizations are seeking to build a more resilient network, they are in fact trying to build a network that will reduce the costs of failure.

2.2.2 Performance Metrics

Besides cost, it is also important to consider other performance metrics. Performance measures must be considered so that the decision not only reduces cost but also provides an acceptable level of performance. Performance metrics may include reliability, probability of major damage, asset condition and asset capacity. These metrics will vary depending on the specific type of infrastructure. Some possible performance metrics are listed below:

- **Reliability**: The percentage of time that infrastructure is operational.
- **Connectivity**: The ability of infrastructure elements to form a continuous path from one location to another.
- **Capacity**: The amount of (electricity, water, wastewater, cars, data, phone calls etc.) that the infrastructure can handle.
- **Extent of Service**: The percentage of customers that have service.
- **Probability of disruption**: The likelihood of a disruption occurring
- **Consequences of disruption**: The consequences of a given disruption.

Performance metrics are important because they help create a bigger picture of how the infrastructure is actually performing its designated function and how that performance may be affected by adverse events.

2.3 Challenges with Resilience Attributes and Metrics

Although the attributes and metrics described above can be easily understood, they are not easily combined to form one exact picture of what a resilient system is. The attributes and metrics represent various facets of resilience, but do not describe resilience completely. Most of the attributes are not easily quantifiable (Jackson 2010). Even for the metrics which are quantified, there is no one way in which they could be combined into a single metric indicative of resilience. Another challenge is that many failures are due to unpredictable events and unpredictable consequences of such events. This stems from the great uncertainty involved in rare events and complex systems. For the metrics especially, these unpredictable events are often left out of an analysis. Despite the challenges in directly measuring resilience, these attributes and metrics can be used to inform decisions for more resilient infrastructure.

Chapter 3

EXISTING TOOLS FOR RESILIENCE

Since resilience involves many complex interactions to reduce the likelihood, consequences and duration of disruptions, there is no all-inclusive way to measure resilience or make decisions for resilience. However, various already commonly used tools can be used to inform decisions that enhance infrastructure resiliency. The most universal means to ensure reliability of engineered infrastructure is to follow codes and standards specific to the class of infrastructure and the hazards it faces. Unfortunately, many codes and standards do not consider in detail the risks infrastructure faces, the varied costs of failure and the costs to improve infrastructure performance. Risk assessment is a tool that can be used to better understand the risks and costs of failure. Life cycle cost analysis can be used to understand these costs in the context of the life cycle of the infrastructure. Multi-criteria decision analysis can be used to inform decisions basing them on risk assessment, life cycle costs and performance measures associated with each alternative. This chapter will discuss design philosophies and building codes, risk assessment, life cycle cost analysis and multi-criteria decision analysis. It will also cover their strengths and weaknesses in furthering resilience.

3.1 Design Philosophies

Many of the decisions that most impact infrastructure resilience are made during the infrastructure design process. Because of this, the inputs into the design process and the process itself are major factors in the resilience of engineered infrastructure. There are two major philosophies underlying this design process: reliability based design and performance based design.

3.1.1 Reliability Based Design

Reliability based design is a design philosophy whose primary objective is reducing the probability of failure. In Civil Engineering, design for reliability can be done indirectly using safety factors or directly by actually calculating the reliability of the structure as it is designed. Load Resistance Factor Design (LRFD) is an indirect reliability design method and uses partial safety factors to protect against uncertainty and variability in design loads, material strengths and other parameters. Direct methods solve for reliability directly, modeling all of the inputs as random variables. Both indirect and direct methods for reliable design have their strengths and weaknesses in promoting resilient performance.

3.1.1.1 Existing Codes and Standards

Most existing codes and standards use indirect methods to design for reliability. This means that reliability is engineered indirectly using safety factors as opposed to directly calculating a structure's reliability. The primary focus of most existing codes and standards is to ensure life safety. The International Building Code which sets the standards for most building construction in the U.S. states that it exists to "safeguard public health and safety" (International Code Council 2012). Continuity of operations and reducing economic costs are a secondary consideration, if considered at all (Gould 2003). Existing codes and standards alone are not well suited for implementing resilience, which, beyond protecting lives, seeks to reduce the likelihood, consequences and length of disruptions.

Although existing codes and standards are not specifically intended to promote resilience, they represent what is currently being done to reduce the risk of infrastructure failure. Codes and standards present a good starting point to build resilience and incorporate a number of useful concepts for managing risk.

3.1.1.1.1 Risk Categories

One useful concept in codes and standards is that they make some attempt at gaging the relative importance for a structure. The International Building Code (International Code Council 2012), ASCE 7-10 (ASCE 2010) and other standards separate structures into four risk categories. These categories are defined based on the risk to life, health and welfare associated with their failure (ASCE 2010). The first category represents buildings that are a very low hazard to human life in the event of failure such as temporary storage facilities. The second and third categories include most structures. The fourth category is for essential facilities such as larger hospitals, power plants and police and fire stations (International Code Council 2012). The idea behind risk categories is that more essential facilities should be better designed against snow, rain, wind, seismic and flood hazards.

The existence of different risk categories is helpful, but has major limitations. Risk categories are useful because they provide for a very simple, straightforward means to classify the importance of a structure and design based on that classification. Although this method generally works to make sure more important structures are more resistant to hazards, it does so in a way that cannot possibly balance the higher construction costs with the life, health, economic and financial consequences of failure. Another limitation is that risk categories, like building codes in general, still focus on life safety without much consideration for the direct costs of failure or the indirect costs failure may impose on infrastructure users and the community as a whole.

3.1.1.1.2 Design Basis Event

Many codes and standards focus on designing for some sort of design basis event. For flooding, this is the design flood and is specified by a certain base flood elevation (ASCE 2006). For seismic design, this is done by designing for ground motion magnitudes associated with an earthquake of a given recurrence interval. Various tables, charts and maps exist to find appropriate design events based on the geographic distribution of hazards. Specifying design loads based on a design basis event can be useful to improving structure performance for that given event and similar less severe events.

A limitation of designing for design basis events is that it may account for only one dimension of the hazard. For example, a structure designed for one specific event may not be adequately engineered for an event of a lesser magnitude and longer duration than the design event (such as a longer earthquake). And although a structure may be built against some design event, events exceeding the design basis event may still cause unmitigated catastrophic failure. This can be the case with levees, which offer significant protection from flooding, until the flood level exceeds the design basis event and overtops the levee. At this point the levee may actually just make things worse by trapping the floodwaters in the area it was supposed to protect.

Most codes and standards exist primarily to protect life safety. For the most part, they are very effective in accomplishing this task. However they are not always enough to address the risks that infrastructure faces (Frangopol 2011; Wen 2001). One of the major weaknesses in existing codes and standards is that they are often very prescriptive and do not address in detail the costs of improving resilience or the benefits of avoiding costly infrastructure failures. For critical infrastructure that provides important service, existing codes and standards may be inadequate to address the risks infrastructure faces because the costs of infrastructure disruption are not considered. While existing codes and standards provide an important starting point for building resilience by avoiding life threatening failures, other methods are needed to help infrastructure owners more finely balance the costs and benefits of more resilient infrastructure.

3.1.1.2 Direct Design for Reliability

Direct design for reliability involves actually using the equations that govern failure to explicitly calculate the reliability of the design. Direct design may calculate structural reliability using first moment statistical measures such as mean and standard deviation to describe the input parameters as random variables. More detailed direct design can use full probabilistic measures for all of the inputs (Ayyub and McCuen 2011).

The benefit of direct design is that the actual reliability of the design is much more transparent. Direct design also allows engineers to explicitly consider the probabilistic nature in which loads and material properties actually vary. Compared to indirect design, the disadvantage to direct design is the amount of time, effort, data and computation required to perform an analysis (Ayyub and McCuen 2011). In the context of resilience the more thorough nature of direct design is useful because it can consider the probabilistic nature of the hazard more carefully. Direct design is however limited in aiding resilience because it considers only the reliability of a structure and not the consequences or length of disruption.

3.1.2 Performance Based Design

Performance based design is a newer design philosophy intended to better address earthquake risks. As opposed to conventional codes which enforce only a minimum standard for life safety, performance based design allows building owners to determine how they would like the building to perform in an earthquake. Objectives may include: life safety, continuity of operations, impact to service and restoration of service (Gould 2003). Performance based design represents a major advancement for the engineering design process as it enables building owners to set their own objectives, which can drive resilient performance. However, even performance based design doesn’t provide tools for infrastructure owners to balance the costs of building resilience with the benefits of avoiding failures.

3.2 Risk Assessment

While the design process guides how infrastructure is designed, risk assessment can be used as a tool to inform the design process. Risk assessment can also guide decision-makers in managing risks over the entire infrastructure lifecycle. Risk assessment is especially useful for better considering the potential failure costs that the design process may not account for. Understanding, managing and reducing disaster risks provides the foundation for improving resilience (National Research Council 2012). The international standard on risk management broadly defines risk as “the effect of uncertainty on objectives (ISO 2009).” Risk assessment generally consists of answering the triplet of questions (Kaplan and Garrick 1981):

- What can go wrong?
- What is the likelihood of something going wrong?
- What are the consequences?

In engineering, a simple means to measure risk is to define it as the product of the probability and consequences of an event occurrence (Jenelius et al. 2006; Berdica 2002). More generally, risk can be considered to be a multi-dimensional quantity that comprises event occurrence probability, event occurrence consequences, consequence significance and population affected (Ayyub and McCuen 2011).

3.2.1 Modeling Risk

Natural hazard risk can be modeled by separating it into hazard, exposure, vulnerability and consequences. Hazard describes the hazard agent itself, its probability and magnitude. Exposure examines what assets are subjected to the hazard. Vulnerability considers what the effect of the hazard would be on the assets. Consequences describe the financial and economic costs that damage would cause for infrastructure users and the broader community (Masse et al. 2007; FEMA 2011; Bayraktarli et al. 2005; Straub 2005; National Research Council 2012).

For example the wind risk on a utility pole could be modeled as follows. The hazard would be the wind; specifically, the probability of the occurrence of various wind speeds. For exposure, the entire above ground portion of the utility pole is subjected to the wind hazard. Vulnerability models the damage that high winds could cause to the utility pole. Consequences would include the cost of repairing a broken pole in addition to the costs that a power outage incurs on a community. These costs may be much greater than the cost of the pole itself, especially if the utility pole provides electrical service to other critical infrastructure such as traffic lights, water pumping equipment or hospital facilities.

3.3 Life Cycle Cost Analysis

While risk assessment is useful to calculate the expected failure modes and their associated costs, life cycle cost analysis is useful for putting these costs into the context of the total costs to own a piece of infrastructure over its lifetime. This method can also be adapted to seek cost-effective means to increase infrastructure resilience.

3.3.1 Life Cycle Cost Analysis in General

Life cycle cost analysis is gaining popularity as a method to examine infrastructure decisions. Life cycle cost analysis consists of calculating the total cost of an infrastructure element over the course of its entire life cycle. This cost includes the initial construction costs as well as discounted future costs for maintenance, operations, and end of life cycle disposal. In addition to the costs to the infrastructure owner which are known as agency costs, external costs can also be considered.

External costs comprise user costs and non-user costs. User costs capture the impact that inefficient, degraded or disrupted infrastructure performance has on the users of the service (FHWA 2002). For example transportation infrastructure user costs may include the cost to drivers of traffic delays, noise, comfort, health effects, risks and vehicle wear. Non-user costs capture the impact of infrastructure function on the broader community and may include economic and environmental costs to nearby residents and businesses.

3.3.2 Life Cycle Cost Analysis for Resilience

Although it is a more general tool, life cycle costing can be valuable in helping infrastructure owners make infrastructure more resilient. Life cycle cost analysis is useful for disaster resilience when it accounts for the cost of retrofit activity and the expected value of the lifecycle costs due to hazard risk (Wen and Kang 2001; Kang and Wen 2000). Although retrofit or mitigation activities incur near-term agency and user costs, they can improve resilience by reducing the failure costs due to an extreme event and they may also reduce maintenance costs over the lifecycle of the infrastructure.

The costs of infrastructure failure can be incorporated into a life cycle cost analysis by using outputs of a risk assessment as an input to the life cycle cost. The failure cost can be accounted for by adding the annual expected value of failure as an annuity to the life cycle cost calculation.

Lifecycle costs due to hazard risks can include agency, user and non-user costs. Agency costs due to hazard risk may include lost earnings due to disruptions, the value of destroyed infrastructure, costs required to repair damaged infrastructure and costs to enact emergency measures. User costs can be wide ranging. For disrupted transportation infrastructure that can be circumvented, the user cost may be the additional time, vehicle wear, and fuel for users to get to their destinations. For businesses without electricity, the user cost may be either the cost of running generators or the value of lost business.

User and non-user costs can be large and difficult to estimate beforehand. For example, after the Northridge California earthquake, it is estimated the closure of the I-10 freeway cost users a million dollars a day, while regional transport disruptions in general cost local businesses 1.5 billion dollars (Chang et al. 1998). The power outages in Manhattan during Hurricane Sandy not only affected residential customers and businesses but also impacted communications networks, led to hospital evacuations and disrupted the financial industry (PlaNYC 2013). The calculation of these costs can become very complex. In these cases it would be very easy to greatly underestimate the user and non-user costs of a disruption.

Life cycle cost analysis can be a useful tool for evaluating the cost effectiveness of alternatives for hazard mitigation. Seeking to reduce lifecycle costs makes it possible to balance the costs of mitigation measures with the benefits of reducing extreme event impact costs.

3.4 Multi-Criteria Decision Analysis

Although reduced lifecycle costs are good for resilience, simply minimizing life cycle cost will not always ensure that resilient decisions are made. Other criteria such as infrastructure performance must also be considered. Infrastructure performance may comprise factors such as condition, safety, reliability and others as necessary. Any resilient infrastructure decision must balance the life cycle cost with infrastructure performance to ensure that minimizing costs does not cause unacceptable asset condition or decreased reliability and resilience (Frangopol and Liu 2007).

Once risk assessment is used to estimate the risks and these are incorporated into the life cycle cost analysis, infrastructure operators are still left with a decision to make. Risk assessment and life cycle cost analysis alone may be insufficient to make resilient decisions; multi-criteria decision analysis can be used as well (Bier et al. 1999; Frangopol and Liu 2007). Both the expected lifecycle costs and infrastructure performance affect the decision. This becomes a multi-criteria decision analysis problem.

Like risk assessment and life cycle cost analysis, multi-criteria decision analysis is a large field and a multitude of methods exist. In a multi-criteria decision problem, a decision maker is presented with a decision in which there are dissimilar criteria such as performance and cost that cannot easily be compared one to another. For infrastructure, the criteria will consist of costs (construction, retrofit, maintenance, lifecycle total, failure and indirect costs) and performance measures (condition, safety, reliability, capacity, time to recovery). In many cases these criteria will be uncertain and uncertainty must also be considered. Simple decision rules, multi-attribute utility theory, the analytic hierarchy process, multi-objective programming and many other methods can be useful to aid in selecting an alternative (Greco 2004).

3.5 Summary

There are a variety of already existing tools that can be useful in better informing decisions for infrastructure resilience. Although existing design philosophies and modern codes and standards cannot ensure resilience, they are an important starting point to prevent failures and protect health and safety. Other tools are better suited to further balancing the costs and benefits for decisions. Risk assessment allows analysts to quantify the risks that infrastructure faces. Life cycle cost helps to compare and balance the costs of retrofit and the benefits of avoiding infrastructure failures. Multi-criteria decision analysis tools can be useful to aid decision-makers in making decisions that involve multiple criteria inherent in resilience problems. Together, these existing methods provide the basic tools needed to make decisions for resilient infrastructure.

Chapter 4

THE CHALLENGE OF UNCERTAINTY

While infrastructure design, risk assessment, life cycle cost analysis and other tools are useful for approaching infrastructure risk, these tools can have difficulty with the uncertainty. Uncertainty is a lack or incompleteness of information or understanding (National Research Council 2009). It could also be considered the potential for surprise (Ben-Haim 2006). The distinction between risk and uncertainty can be subtle. Risk refers to a situation in which the probabilities of occurrence are known (Haimes 1998). For example while the outcome of a rolling fair die, is not known, it is known that there is a 1 in 6 chance of the die landing on any given number 1 through 6. Uncertainty refers to a situation in which the probabilities describing the system are unknown. Since risks are known, they can be bet on profitably. This is the basis for the insurance industry. Uncertainties, however, are unknown. Uncertainty poses a major problem for the pursuit of resilience. How can infrastructure be more resilient to hazards with unknown probabilities, unknown consequences or completely unknown and unexpected hazards?

Uncertainty presents major challenges in the development of infrastructure resilience. When neglected, uncertainty can greatly undermine the techniques of infrastructure design, risk assessment and life cycle cost. The objective of this chapter is to explore the uncertainties associated with infrastructure risk and identify possible methods to work with uncertainty. This chapter will first discuss general classifications of uncertainty and then sources of uncertainty for infrastructure systems in particular. The chapter concludes with a discussion of methods for handling the uncertainties present in infrastructure systems.

4.1 Classifications of Uncertainty

Fundamentally there are two types of uncertainty. Aleatory uncertainty results from natural variation or randomness in nature. Epistemic uncertainty occurs because we do not have enough knowledge to fully understand the phenomena. The major distinction between aleatory and epistemic uncertainty is that epistemic uncertainty may be reduced by committing more resources to understanding the phenomena while aleatory uncertainty cannot be reduced (Rausand 2011).

The problem with uncertainty is that it causes our representations or models of phenomena to deviate from that which is actually observed. This poses a challenge for infrastructure resilience decisions which are largely based on models of hazards, risk, infrastructure performance and others. A variety of contributors to uncertainty are described below (Rausand 2011).

- Completeness uncertainty arises as a consequence of the analysts not considering everything that should be considered.
- Model uncertainty is due to the inadequacy of models to represent real world phenomena.
- Parameter uncertainty is caused by limited accuracy or applicability of the input data.
- Consequence uncertainty is caused by not knowing the potential consequences of an event of interest.
- Calculation uncertainty comes from errors accumulated during calculations.
- Competence uncertainty comes from poor analysis skills.

- Resource uncertainty is due to the fact that the organization lacks the time, money or other resources needed to collect more or better data and do more in depth analysis.

4.2 Sources of Uncertainty for Infrastructure Systems

The categories of uncertainty listed previously can be found throughout the analysis of infrastructure risk. The sources of uncertainty in modeling infrastructure system risk and resilience can be sub-divided into the hazard, vulnerability and consequence components commonly used in risk assessment.

4.2.1 Hazard Uncertainties

Uncertainty in the nature of the hazard event is a large contributor to the overall uncertainty in infrastructure risk and resilience. Uncertainty about the nature of the hazard stems from the assumption of stationarity and the fact that many of the hazards of interest are extreme events.

4.2.1.1 Stationarity

A common assumption in many risk assessments and in other analyses is the assumption of stationarity, that past history will be indicative of what will happen in the future. This assumption, however, is not always correct. The assumption of stationarity for non-stationary hazards thus introduces model and parameter uncertainties as the models used to model hazards may not represent future behavior.

Historical data may not always represent what the risk will be in the future. Although historical data may indicate that a given flood condition has a 1 in 100 chance of occurring, this statistic may be inaccurate. The probability of flooding may be different now due to increased development upstream or new flood protection infrastructure that while reducing more frequent, less severe flooding may make catastrophic flooding more likely. The chances of flooding may also change because of changes in weather and climate patterns (Milly et al. 2008).

For meteorological hazards such as hurricanes, tornadoes, floods, severe storms and wildfires the assumption that past climate is indicative of future climate is increasingly being called into question. It is now widely accepted that earth's climate is non-stationary (Karl et al. 2009). Certainly as climate changes, the occurrence of extreme events will also change. However there is a great deal of uncertainty associated with all of this. First of all, there is uncertainty as to how the average global climate is changing as whole. For example, recent estimates for global sea level rise by 2100 vary from up to 2.5 feet to up to 6.5 feet (National Research Council 2010). Beyond this, to make infrastructure decisions, decision-makers need information about how local climates are anticipated to change. Localization of global climate models to make local forecasts, further introduces uncertainty. This is further complicated by the introduction of extremes. While much of the climate change research offers information about how averages may change, infrastructure decision makers are more interested in the frequency and magnitude of extreme events. Researchers have discovered that changes in averages due to climate change are not indicative of the frequency or severity of extremes (Karl et al. 2009).

For non-stationary hazards, the assumption of stationarity can introduce large amounts of uncertainty into the analysis. The assumption of stationarity introduces model uncertainty and parameter uncertainty as models and inputs that may not be applicable are used to model future hazards.

4.2.1.2 Rare and Extreme Events

The fact that most hazard events of interest are extreme and rare events further adds uncertainty to the problem. Extreme events are incidents with either an extremely low or high magnitude. Rare events are events that have a very low frequency of occurrence (Pinto and Garvey 2012). Although rare extreme events are by definition unlikely, they cannot be ignored due to their potentially large impact.

Extreme events are important in approaching risk and resilience because of their potential for having a great impact. In systems in which the magnitude of a parameter is associated with loss or damage, an extreme event will also cause a large negative impact. Most natural hazards can be considered in this way. For flood hazards, damage is strongly associated with precipitation and tide. An extreme high tide event or an extremely intense or long precipitation event generally causes more flooding and more damage. For earthquake hazards, damage is associated with extreme ground motion, which occurs very rarely.

The challenge in dealing with rare events is their low frequency of occurrence. Since these events are rare, there is less data about their occurrence. For meteorological and hydrological hazards, most regions lack 100 years of reliable wind, rain and flood data. This introduces uncertainty into the calculation of the 100 year storm, because this estimate will be based on just one data point. Even more uncertainty is introduced when estimating the intensity of a 250 year storm when there is only 100 years of data available.

In many cases infrastructure must be resilient against hazards for which there may be no record of previous occurrence. Since uncertainty is ignorance or lack of knowledge, it is easy to lack knowledge regarding extreme events that have no recorded history of ever having occurred in a given location. Many of the worst disasters in recent history have been unprecedented. The 2012 Hurricane Sandy, 2005 Indian Ocean Tsunami and the 2011 Japan Tohuku earthquake and tsunami were all extreme events of such a magnitude that has not been recorded in recent history. These and other extreme and rare events are surrounded by uncertainty, as there is sparse information indicating what extremes could possibly happen.

4.2.2 Vulnerability Uncertainties

There are also uncertainties about infrastructure vulnerability to damage from hazards. Much of the uncertainty about vulnerability may be due to resource uncertainty as budgets are often too tight and systems are too complex to be analyzed in full detail. Parameter uncertainty can also be introduced as the infrastructure's initial condition may not be completely known. Beyond the time and expense to perform frequent, thorough inspections, many parts of the infrastructure are unseen and cannot easily be examined. This makes detailed infrastructure condition impossible to know.

4.2.3 Consequence Uncertainties

There is a great deal of uncertainty in the consequences of a disruption. This is partially due to the ever increasing complexity and inter-connectedness of our society which makes it very difficult to build a model that captures the complex interactions and decisions being made within a community. Another challenge for consequence uncertainty is completeness uncertainty. Since there are almost limitless consequences of infrastructure failure and society has only experienced a fraction of them, there is a good chance that analysts have not thought of all of the possibilities.

4.3 Methods for Working with Uncertainty

The many sources of uncertainty in modeling infrastructure systems and their interactions with hazards and their communities make it necessary to work with and consider uncertainties in the analysis of infrastructure resilience. A number of methods already exist to handle uncertainty.

4.3.1 Extreme Value Theory

Extreme value theory is a mathematical and statistical approach used to extrapolate extreme values from some existing data. For example in the Netherlands, they determined to build a dike system capable of withstanding a 10,000 year flood. To do this they must know what magnitude of flooding has a recurrence of 10,000 years. Unfortunately they only have flood data for 100 years (de Haan and Ferreira 2006). Extreme value theory overcomes this challenge. Extreme value theory uses statistics to model the tail end of the distribution, and then uses that model to extrapolate extreme values that have not yet been measured (Coles 2001). Extreme value theory does this by estimating the first and second derivatives near the boundary of a dataset and then using those derivatives as the basis for extrapolating values outside of the original dataset.

Extreme value theory certainly has its limitations and weaknesses. A core assumption of extreme value theory is that the underlying stochastic process is sufficiently smooth to allow for extrapolation to unobserved values. For natural hazards, this may in many cases be an incorrect assumption. In fact, available data for a hazard may be generated by a completely different process than the process responsible for the extreme event. For example tide elevation data may be used to determine if a coastal location will flood. Most of the fluctuations in tide data are driven by gravitational forces from the moon and the sun. There may be no data at all about the processes that actually cause flooding such as hurricanes or tsunamis. Using extreme event theory to extrapolate the highest water level from tide data cannot capture the extreme high water level because hurricanes and tsunamis are driven by completely different processes.

4.3.2 Info-Gap Theory

Information gap theory is a method which is suitable for handling large amounts of uncertainty. Instead of relying on probabilistic risk estimates, info-gap theory focuses on handling the great amount of uncertainty present. One of the major benefits of info-gap theory is that the only input information required is a single central estimate of what the uncertain parameter of interest could be. Info-gap theory relies on a measure called robustness. Robustness is a measure of the greatest amount of uncertainty present in which the system will still perform in an acceptable fashion. It is desirable to have acceptable operation under as much uncertainty as possible, thus higher robustness is better (Ben-Haim 2006). For example, say that for the utility pole example our criterion was that the utility pole has to have less than a one percent chance of failure. The robustness would represent the largest amount of uncertainty for which the utility pole is still guaranteed to have less than a one percent chance of failure.

4.3.3 Uncertainty Sensitivity Index Method (USIM)

The Uncertainty Sensitivity Index Method (USIM) is used to simultaneously consider risk probabilistically while also accounting for the uncertainty in risk estimates. USIM consists of calculating an uncertainty index that is used to give the decision maker a sense of the sensitivity a given function has to variations in an uncertain parameter. The uncertainty index is calculated by taking the derivative of the cost function with respect to the uncertain input parameter.

While this procedure is relatively simple, it can be useful. The uncertainty index thus helps the decision maker determine the extent to which the outputs are sensitive to the uncertain inputs (Li and Haimes 1988; Haimes and Hall 1977). A limitation is that it does not handle well functions whose derivative has significant changes, such as for exponential or step wise functions.

4.3.4 Bounding Uncertainty

Another approach to dealing with uncertainty is to bound the uncertainty. This approach simply sets bounds on the input parameters of a model, and then uses mapping functions to calculate the bounds for the output parameters. A limitation of this method is that it requires information about the bounds of input parameters which may not be available (Bernardini and Tonon 2010). Unlike the info-gap and USIM methods, which operate with a large amount of ignorance about the input parameter, the bounding method requires that the analyst know the bounds of the parameter.

4.4 Summary

Uncertainty can be very problematic for decision-makers, especially in the realm of infrastructure resilience. Nearly every aspect of resilience has some aspect of uncertainty about it. This is because fundamentally there are many things that are unknown. This is especially the case for complex infrastructure systems which are exposed to rare and changing hazards.

There are a variety of tools that exist to address uncertainty. Extreme value theory, info-gap theory, USIM and bounding are a few of the many methods that exist to address uncertainty. Although these tools exist to address uncertainty, the application of these tools to make resilient decisions can be difficult. Many analysts and decision makers may avoid addressing uncertainties as this complicates the analysis and may make results less clear. Even when such tools are properly applied to address uncertainty, there remain challenges. The uncertainty tools themselves add additional assumptions and may bias results. Uncertainty can be a great challenge to making resilient decisions.

Chapter 5

AN APPROACH TO MAKING RESILIENT DECISIONS

Due to the ambiguous nature of resilience and the complexity and uncertainties of infrastructure it can be difficult to make good decisions that promote infrastructure resilience. This chapter proposes an approach that may be used to inform decisions that strengthen infrastructure resilience. These decisions, like many other decisions, can be made by first defining the problem and identifying objectives, next identifying alternatives, then performing analysis and finally evaluating the alternatives as shown in Figure 1. This chapter explains how this generalized decision process can be adapted to make decisions for resilience by incorporating tools like risk assessment, life cycle cost analysis and uncertainty models into the analysis of the problem.

Figure 1. Steps involved in approach for making decisions for resilience

5.1 Define Problem

The first step is to identify the problem. This is common among many decision-making strategies (Haimes 1998; Morgan 1992). Definition of the problem may include a description of the problem, the hazards faced, the infrastructure involved, the context and the scope.

5.2 Identify Objectives

Objectives identify exactly what the organization wishes to accomplish. Although, generally, everyone wants resilience, it is useful to break the objective of resilience into smaller pieces that can be more easily evaluated. The objectives may be either qualitative resilience attributes or quantitative measures that align with resilience as discussed previously. Other objectives that are not resilience related may be considered as well, such as costs and benefits to the community like maintenance costs, property values and economic development.

Resilience objectives will vary for different stakeholders. For example, an electric utility that wants a more resilient network might have objectives like improving reliability and lowering restoration costs due to outages. Meanwhile a hospital's resilience objective might be to reduce the effect power outages have hospital operations. Although in a broader context, these resilience objectives are self-interested, it is important to realize that self-interested objectives can be the best incentive for a stakeholder to make investments in resilience. Although self-interested resilience seeking may not result in the most resilient option for a community, increased resilience ultimately benefits everyone.

5.3 Generate Alternatives

Once the objectives and criteria have been identified, a set of alternatives can be generated. As a starting point, each alternative should meet applicable codes and standards. Climate change literature (Savonis et al. 2008) identifies three categories of alternatives that could easily apply to many other hazards: protect, accommodate and retreat. Protection involves engineering infrastructure to better resist a hazard or building structures (such as levees) to protect the infrastructure at risk.

Accommodation alternatives consist of altering operations such that when the hazard strikes the impact isn't as large. Installation of pumps to remove seawater or plans to reroute traffic after an event are possible accommodation activities. Retreat alternatives seek to avoid the hazard (Savonis et al. 2008). Outside of these categories there are alternatives such as a do nothing alternative, the business as usual alternative and others.

5.4 Perform Analysis

Once the alternatives have been identified, analysis will be required to determine how well each alternative meets the specified objectives. This analysis will vary in scope and depth according to the needs and resources of the stakeholders. Analysis should be done iteratively, starting with a simple analysis, and gradually introducing more depth and detail such that there is enough information to make a decision. The analysis should be the simplest possible analysis needed to make the decision but no simpler (Morgan 1992). Multiple analyses may be conducted to address a series of questions. For example, first an analysis may be performed to determine how much should be spent on mitigation; next an analysis may be used to narrow down a large number of competing alternatives; then an analysis could be done to compare the most viable alternatives; finally an analysis may be conducted to fine tune a selected alternative (for example, how tall should levees be built). Regardless of the exact nature of the analysis, the analysis should address uncertainties in some way.

Analysis can be divided into four parts as seen in Figure 2. These parts are performance requirements, decision variables, uncertainty model, and system model. The performance requirements are a clear quantitative or qualitative statement of objectives that can be determined and compared. The decision variables are a set of parameters that represent the choices the decision-maker could make. The uncertainty model provides uncertain inputs to the system model. The system model is a function that models the performance of the infrastructure system to see how close the expected performance is to the performance requirements. When constructed properly, the decision variables and uncertainty model will be input into the system model to determine if the decisions can meet performance requirements. The concept of using performance requirements, a system model and an uncertainty model comes from

Figure 2. Steps to perform an analysis.

info-gap theory (Ben-Haim 2006) but it will be seen that this framework can be easily adapted to use with other types of uncertainty.

5.4.1 Performance Requirements

The first step in performing an analysis is to develop a set of performance requirements that the infrastructure system is expected to meet. The performance requirements take the objectives of the project and list them in concrete terms so that the performance of each alternative can be easily compared. For qualitative attributes of resilience, performance requirements can be simple statements such as: the system should be relatively easy to repair or the system should allow for human intervention in case of interruption. Quantitative performance measures should be assigned as some inequality. For example, the agency costs of a windstorm must be less than $10,000 or the availability of the data center must be greater than 99.9%. To begin with, all performance measures should be assigned to some value. However, as the analysis goes on the analyst may go back and modify their performance requirements as needed.

5.4.2 Decision Variables

The decision variables represent the choices that the decision-maker can make. These may be simple mutually exclusive options, such as the decision maker can pick A, B or C. They may also be options that can be combined in different ways. Decision variables could also be continuous quantities, such as the amount of money to spend on mitigation or the flood elevation to use as the design flood.

5.4.3 Uncertainty Model

The uncertainty model describes the uncertainty in the input parameters to the system model. There are a number of different types of uncertainty models which may be used. Bounding, probabilistic, and info-gap uncertainty models may be used to model the uncertainties in the problem.

5.4.3.1 Bounding Uncertainty Model

The bounding uncertainty model is a simple model that can be used to represent the uncertainty present in a resilience problem. In the bounding method, bounds are selected to represent high and low values within which the true value is expected to lie. When using a bounded uncertainty, the ambient uncertainty inputs provided to the system model are represented as bounds, and then functions within the system model produce a set of bounds to represent the system’s performance. An advantage of the bounding model is that it allows for a large amount of uncertainty by allowing the analyst to provide bounds to the input values. The bounds for the corresponding results can be both good and bad. In cases in which the bounds for the result are quite large, the results of a bounded analysis may provide no direction for actually making a decision. However, the advantage of the bounded analysis is that it reduces the chances of the decision makers coming to a decision based on incorrect estimates of central tendencies or parameter distributions.

5.4.3.2 Probabilistic Uncertainty Model

A probabilistic uncertainty model uses probability distributions to represent uncertain inputs into the system model. When a probabilistic uncertainty model is used, the system model must use simulation or analytic methods to transform the input probability distributions to produce an output. In many cases the output may also be a probability distribution, although it is possible to produce other outputs such as an expected value.

Probabilistic models are ideal for modeling inputs in which the risks are well-known. However, they can be problematic for modeling uncertain parameters. To use a probabilistic model for an uncertain parameter, the analyst must make some assumption as to the distribution of the parameter. When a distribution is not known, a common technique is to assume that all possible outcomes are equally likely or evenly distributed. Another technique is to use a triangular distribution or normal distribution to model a parameter for which bounds and a central estimate are known. In these cases the analyst assumes that it is more likely for the parameter to fall close to the central estimate. The benefit of these methods is that they may provide a more precise answer than the bounding method. However, this comes at a cost, as the result of the probabilistic model comes only by making assumptions about the distribution of the parameter, which is actually not known.

5.4.3.3 Info-Gap Uncertainty Model

The info-gap uncertainty model is useful for modeling uncertainty in a way that makes few assumptions about the central tendencies, bounds, or distributions of the input parameters. For an uncertain parameter, x, the info gap uncertainty model is represented by the equation below:

$$\mathcal{U}(\alpha, \tilde{x}) = \{x: |x - \tilde{x}| \leq \alpha\}$$

In this equation x is the parameter's actual value (which is unknown), and $\tilde{x}$ represents the best estimate for x using the best available model. The uncertainty model is the set of all possible values of x that deviate from $\tilde{x}$ by no more than α. The value of α is an indication of the amount of uncertainty. A large α value indicates higher uncertainty and will produce a larger set of possible x values. When an info-gap model is used with the system model the result will produce the robustness values for the performance requirements. The robustness value for the performance requirements is a measure of the maximum amount of deviation from the nominal values that will still guarantee that the performance requirement is satisfied.

5.4.4 System Model

The system model is used to model of the performance of the infrastructure element being examined. Since there is no universal means for measuring resilience, the system model is used to model metrics of the system that are related to resilience. The variables modeled by the system model are determined by the performance requirements.

Generally, the system model is a function, known as the reward function, which has two inputs. The first input is the decision vector q which reflects the decision maker's choices. The ambient uncertainty u represents the uncertain inputs that influence the performance. Using these two inputs, the reward function is then used to calculate performance.

$$Performance = R(u, q)$$

There are many possibilities for developing the system model. The system model could be a risk assessment, life cycle cost analysis, or any other suitable tool to model system characteristics that are associated with resilience.

5.4.4.1 Risk Assessment

Risk assessment can be used as part of the system model to calculate the probability, consequences or risk of infrastructure disruption for each alternative. This may be done with varying complexity depending on the needs of the problem. Figure 3 shows a way in which the risk assessment may be organized to provide the outputs needed to make a decision.

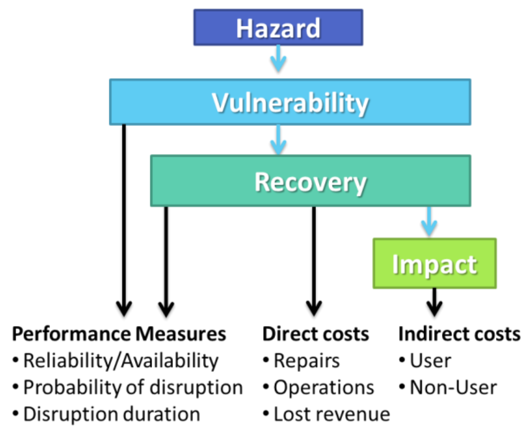

Figure 3. A risk assessment methodology.

In this risk assessment methodology the hazard function models the hazard, its probability and magnitude. The vulnerability function models infrastructure damage due to the hazard. The recovery function models how long it takes to restore service and at what cost to the infrastructure owner. Impact models the consequences infrastructure disruption has on users and non-users. Inputs used for risk assessment will vary according to the level of detail needed. Inputs may come from expert elicitation, historical data, and models (Bier et al. 1999). These inputs will be uncertain inputs to the system model. Outputs include performance measures like reliability and the expected value of failure or disruption costs over the lifecycle.

5.4.4.2 Life Cycle Cost Analysis

Life cycle cost analysis principles may be used alone to form the system model, or may be used in conjunction with risk assessment or other models. When applied, life cycle cost analysis takes uncertain inputs and a decision vector and returns the life cycle costs as the system performance. In most cases it will be necessary to combine life cycle cost analysis with risk assessment. In this case the life cycle cost calculation uses the expected value of the costs of failure from the risk assessment as an input. Like risk assessment, the level of detail needed for life cycle cost calculation may vary. A simple lifecycle cost may rely on estimates for construction, maintenance, and failure repair costs from design and maintenance engineers. More in depth life cycle cost analysis may involve examining asset management databases or utilizing models to get more accurate costs for each alternative.

5.4.4.3 Other Functions

Beyond life cycle cost analysis and risk assessment techniques, a host of other functions may be used to form the system model. Generally the system model is simply the necessary outputs to evaluate performance requirements given decision variables and uncertain inputs. Depending on the needs of the analysis, the system model could directly or indirectly model the effects of external forces acting on individual structural elements.

5.4.5 Evaluate Results

The final step is to evaluate the results. Various metrics that can be used as proxies for resilience such as lifecycle costs and expected performance in terms of reliability, disruption times, safety, and condition can be used to evaluate the alternatives. Depending on the needs of the organization, this decision may be guided by some combination of professional judgment, precedent, policy, and multi-criteria decision analysis methods. Resilient decisions will meet the three outcomes of reducing failure probabilities, reducing consequences from failures, and reducing time to recovery (Bruneau et al. 2003). Multi-criteria decision analysis considering owner preferences and community needs will determine how these are balanced against costs to increase resilience in a cost effective manner. The process is complete when a decision can be made. If there is too much uncertainty to make a decision or if further questions remain it may be necessary to perform multiple analyses to fully explore the effect of the uncertainties and decision variables on system model performance.

Chapter 6

PRIME HOOK ROAD DELAWARE CASE STUDY

6.1 Background

Prime Hook Road is a local coastal road that provides access to a community of 200 homes on Delaware Bay in Kent County, Delaware. The road is an embankment crossing a marsh as shown in Figure 4. This road will be used as a case study to demonstrate the application of the approach to decision making developed in the previous chapter. The five mile long road is owned and maintained by the Delaware Department of Transportation (DelDOT). A mile long segment of the road has major flooding problems as water from the bay begins to cover the roadway when the water level gets a little higher than high tide. In the three years from 2010-2012, the road has been rebuilt twice and was closed more than 17 days due to flooding. The road provides the only public access to the community, so when it floods, DelDOT pays about $1000 a day to provide access to the community via a privately owned property. Possible long-term alternatives are to build a bridge, to elevate the road, to continue to repair road after each flood, or to abandon Prime Hook Road and purchase a part of the privately owned property to provide access to the community.

Figure 5. Prime Hook Road Highlighted in Red. © 2013 Google

Figure 4. Prime Hook Road. Photo: Erik Archibald 2013

6.2 Objective

In this case study the objective is to provide access to the coastal community in a cost effective manner, while considering uncertainties due to sea level rise and climate change. This objective lends itself to two metrics: access reliability and total agency life cycle cost.

The access reliability metric measures how reliably an alternative provides access to the community. While total user life cycle cost may be a more comprehensive measure of the road’s impact on the community, it is much easier for decision makers to think about reliability (e.g. the road will be usable 358/365 days a year) than it is for them to consider user costs (e.g. road closures will cost residents $300,000 in a year).

The total agency life cycle cost is a measure of the cost-effectiveness of each alternative. This metric was selected because the decision-maker in this case is the Delaware Department of Transportation and they are certainly concerned about what the road will cost them.

These objectives form a reasonable though imperfect model of resilience. Improved access reliability and smaller agency life cycle costs are indicators of reducing failure probabilities and consequences, making the community both less likely to be disrupted and less affected when disruptions occur.

6.3 Alternatives

A number of possible alternatives that could meet the above objectives will be evaluated for the above mentioned metrics. The following are alternatives that are considered for this scenario:

1. Continue to maintain the road as it has been historically, making repairs as necessary when it floods.
2. Use lightweight fill to elevate the road surface to reduce flooding.
3. Build a bridge structure to elevate the road so it doesn't flood.
4. Purchase a small piece of private property to create an alternative route, and abandon Prime Hook Road.

6.4 Qualitative Analysis

To be effective the analysis should be as simple as possible. The analyst should start out with a simple analysis and then move on to more complex methods only as needed to provide the decision-maker with sufficient information to make a decision. For this example, the simplest possible analysis is a simple qualitative analysis of the costs and reliability of each option given uncertainty in sea level rise. Once a simple qualitative analysis is used, a slightly more in depth quantitative analysis is performed to obtain more information. A qualitative analysis may be done simply using very rough qualitative estimates of the inputs and outputs of the system model.

6.4.1 Performance Requirement

For this case study, the performance requirements and system model use the metrics of access reliability and life cycle cost. While a qualitative scale will be used for the analysis, the scale can also be mapped to number values. The access reliability scale can be mapped to values between 0 and 1 representing the percentage of time the road is open. The life cycle cost can be expressed as a dollar amount. These metrics may be put on a qualitative scale as seen in Table 1.

Table 1. Qualitative Scales for Performance Requirements

Agency Life Cycle Cost Qualitative Scale	
Low	< \$400k
Medium	\$400k– \$1500k
High	\$1M – \$3M
Very High	> \$3M

Access Reliability Qualitative Scale	
Very Poor	< 0.85
Poor	0.85 – 0.95
Ok	0.95 – 0.98
Good	0.98 – 1.00

Qualitatively the performance requirements are:

- Total Agency Life Cycle Cost < Medium
- Access Reliability = Good

Values that satisfy the performance requirements are highlighted in green in Table 1.

6.4.2 Uncertainty Model

For this problem, sea level rise was designated as the only uncertain variable of interest. Sea level rise may also be represented on a qualitative scale as seen in Table 2. Since this problem uses an analysis period of 30 years, the scale below for sea-level rise represents the average sea level over the next 30 years.

Table 2. Qualitative Scale for Uncertain Sea Level Rise

Sea Level Rise Scale	
No SLR	< 1 ft
Moderate SLR	1 ft – 2 ft
High SLR	> 2 ft

6.4.3 System Model

Now that the performance requirements and uncertainty model have been identified, the system model can be evaluated. The system model can be evaluated mentally using the analyst's judgment, mathematically using rough estimates, or logically using a set of simple rules. In this case the system model was evaluated based on the analyst's judgment, using bounding where the analyst was uncertain exactly how an alternative would perform.

6.4.4 Results

The results of the analysis are represented in Table 3, Table 4, and Table 5. Each table depicts the qualitative outcome for each alternative, given different values for the uncertain sea level rise. The tables are colored according to whether or not they meet the performance criteria, solid green indicates the alternative would meet the criteria, while light green indicates that maybe it would meet the criteria.

Table 3. Evaluation of Access Reliability

Alternative	Access Reliability		
	No SLR	Moderate SLR	High SLR
As Usual	Mediocre - Good	Poor-Mediocre	Very Poor
Lightweight Fill	Good	Ok-Good	Ok - Good
Bridge	Good	Good	Good
Alternate Path	Good	Good	Ok - Good

Table 4. Evaluation of Agency Life Cycle Cost

Alternative	Agency Life Cycle Cost		
	No SLR	Moderate SLR	High SLR
As Usual	Low	Medium–High	High–Very High
Lightweight Fill	Medium	Medium–High	High – Very High
Bridge	Very High	Very High	Very High
Alternate Path	Low	Low	Low

The two tables above can be super-imposed to determine which alternatives meet both criteria, under the greatest amount of uncertainty.

Table 5. Overall Evaluation

Alternative	Meets Performance Requirements?		
	No SLR	Moderate SLR	High SLR
As Usual			
Lightweight Fill			
Bridge			
Alternate Path			

From the tables above, it is seen that the lightweight fill and alternate path alternatives are the only two which can meet both criteria. However, with the current level of detail in the analysis it is unclear exactly how their costs compare and whether or not either of them could possibly meet the performance requirements for a high amount of sea level rise.

6.5 Quantitative Analysis

If the qualitative analysis is insufficient to make a decision, a quantitative analysis may be performed to get more details. Although it is wise to eliminate alternatives that obviously won't work prior to a quantitative analysis, in this case the less desirable alternatives were left in to show how the quantitative results compare to the qualitative results

6.5.1 Performance Requirements

The performance requirements are the requirements that the infrastructure system must fulfill. These requirements are not fixed, and may be adjusted during the process of analysis as needed. For this example there are two performance requirements:

Total Agency Life Cycle Cost < $1.8M over 30 year lifetime

Reliability > 0.98 (closed less than 7 days a year)

6.5.2 Uncertainty Model

The uncertainty model expresses the form of the uncertain inputs to the system model. All of the costs are subject to some degree of parameter uncertainty. The classification of floods into different categories, and then subsequently calculating a probability, repair cost, and closure duration for each introduces model uncertainty.

However, in this case it appears as though the greatest uncertainty lies in the potential for the flooding hazard itself to vary significantly from how it has behaved in the past. This potential is largely due to climate change which may cause a different mean sea level, as well as different storm return periods and intensities.

Since uncertainty in sea level rise is the greatest uncertainty, and that which concerns decision makers the most, the uncertainty model will model only the uncertainty due to sea level rise. The uncertain sea level rise is modeled using an info-gap uncertainty model as seen below:

$$\mathcal{U}(\alpha, \tilde{h}) = \{u: |h - \tilde{h}| \leq \alpha\}$$

Where:

$h =$	The actual value for sea level
$\tilde{h} = 0ft$	The current assumption for sea level
$\alpha =$	The horizon of uncertainty

6.5.3 System Model

The system model is comprised of two equations: one for calculating access reliability and another for calculating total agency life cycle cost.

The access reliability is calculated as the percentage the life cycle in which the road is functional.

$$R = \frac{365 - D_{closed}}{365}$$

Where:

$R =$	The access reliability
$D_{closed} =$	The average number of days access is closed in a year

The number of days which the access is closed is the sum of the product of the probability of each type of event and the average closure length associated with that event.

$$D_{closed} = \sum_{i=0}^{n} P_{i,q} \cdot N_{i,q}$$

Where:

$N_{i,q} =$	The number of days of closures associated with the ith event
$P_{i,q} =$	The probability event i occurring, for alternative q
$i = 0,1,2,3$	0 is a small flood event, 3 is for major event

So for example, if for the elevated road option there is a 1% chance of a major flood causing a 4 day closure and a 5% chance of a minor flood causing a 1 day closure, then the expected length of closures would be:

$$D_{closed,ele} = P_{0,ele} \cdot N_{0,ele} + P_{1,ele} \cdot N_{1,ele}$$

$$D_{closed,ele} = 0.05 \cdot 1\ day + .0.01 \cdot 4\ day$$

The total agency life cycle user cost is a function of the selected alternative, q, and the costs associated with that alternative. More specifically the total agency life cycle cost for a particular alternative is the sum of the initial cost, the maintenance cost, and the failure costs of that alternative over the course of its lifecycle.

$$LCC_q = C_{init,q} + C_{maint,q} + C_{failure,q}$$

Where:

$C_{init,q} =$	The initial cost of alternative q
$C_{maint,q} =$	The maintenance cost of alternative q for the entire lifecycle
$C_{failure,q} =$	The total failure cost for the alternative over its lifecycle

The failure costs over the course of the life cycle can be represented as the sum of the product of the probability and cost of a number of different types of failure.

$$C_{failure,q} = \sum_{i=0}^{n} C_{i,q} \cdot P_{i,q} \cdot t$$

Where:

$C_{i,q} =$	The cost of failure i for alternative q
$P_{i,q} =$	The probability of failure i, for alternative q
$t =$	The analysis time period for life cycle cost
$i = 0,1,2,3$	0 is a small flood event, 3 is for major event

6.5.4 Results

The quantitative analysis was done using the equations as previously described in the analysis. Additional assumptions and calculations can be found in Appendix A. The main output of this analysis is the graphs presented in Figure 6 below, which represents how the performance of the two metrics is affected by the uncertainty in the sea level rise (where the-x axis represents sea level rise in feet).

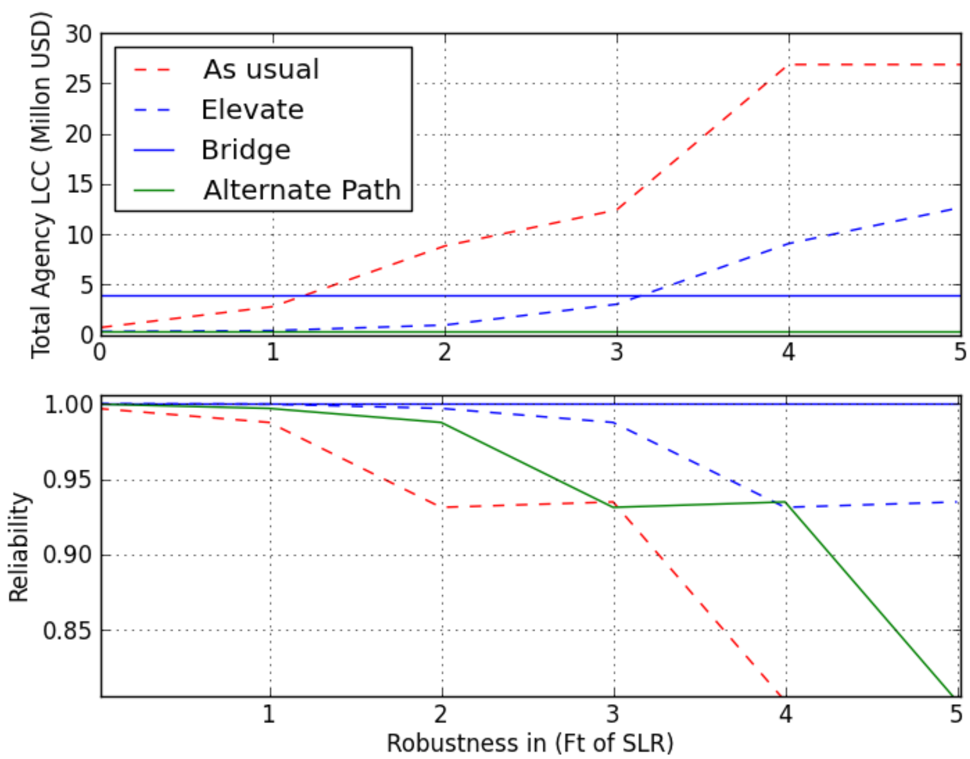

Figure 6. Life Cycle Cost and Reliability Performance Under Uncertainty

The graphs in Figure 6 above quantitatively represent the same characteristics described by the qualitative result tables. In this graph it can be seen that generally as uncertainty in feet of sea level rise increases, reliability decreases and life cycle cost increases. This graph can be useful for comparing alternatives. To determine which alternatives are more resilient, it is necessary not only to look for one with a lower life cycle cost and higher reliability but also one that is sufficiently robust against increasing uncertainty in sea-level rise. For this case study it can be seen that continuing with the as usual maintenance could be very affordable and reliable if there is certainty that sea level rise does not occur. However, if sea level rise does occur this option quickly becomes very expensive and unreliable. Alternatively, building a bridge is an option that appears to be very expensive due to its high initial cost. However, if there ends up being great uncertainty in the amount of sea-level rise, building a bridge would be both the cheapest and the only reliable option.

This case study demonstrates how the approach developed in Chapter 5 can be useful to informing real decisions for infrastructure resilience.

Chapter 7

BROOKLYN-BATTERY TUNNEL CASE STUDY

7.1 Background

The Brooklyn-Battery Tunnel, officially known as the Hugh L. Carey Tunnel connects the New York City boroughs of Manhattan and Brooklyn. The tunnel consists of twin tubes that connect portals in lower Manhattan and Brooklyn. The tunnel is the longest continuous underwater vehicular tunnel in the United States, measuring 9,120 feet from end to end (Toll Roads News 2012). Construction of the tunnel began in 1940; the tunnel first opened to traffic in 1950 (MTA 2013). The tunnel is operated by the Metropolitan Transportation Authority, or MTA, which is governed by New York State. In 2011 the tunnel had an average toll of $5.30 and an average daily traffic of 45,000 vehicles (Toll Roads News 2012). In October 2013 the toll for cars was $5.33 for cars with an electronic pass and $7.50 for those paying with cash (MTA 2013). Alternative paths across the East River from Brooklyn to Manhattan include the Brooklyn Bridge and the Manhattan Bridge, both of which are free.

Brooklyn Battery Tunnel

Figure 7. Map of New York City with Location of Brooklyn Battery Tunnel. Map Data © 2013 Google

7.2 Problem

Prior to Hurricane Sandy, the tunnel had never had a problem with flooding. Both portals are situated such that floodwaters have never reached the tunnel in the past. Unlike many other tunnels in New York City, the Brooklyn Battery Tunnel is constructed through bedrock, and is not affected by groundwater leakage (CBS New York 2012). In 2012 the tunnel was severely impacted by Hurricane Sandy. A record 17 foot storm surge flooded lower Manhattan, sending an estimated 86 million gallons of water into the tunnel (Toll Roads News 2012). About two thirds of the tunnel flooded, stretching from the Manhattan portal and extending past the tunnel ventilation building at Governor's Island that is located roughly in the middle of the tunnel. The tunnel was completely closed for 15 days as crews worked to restore the tunnel to serviceable condition. In addition to pumping out the water and cleaning the tunnel, crews had to repair ventilation, lighting, security cameras, communications, and power systems before the tunnel could resume operation. Full service resumed 22 days after Hurricane Sandy struck (Toll Roads News 2012).

Figure 8. Flooded Manhattan portal of Brooklyn Battery Tunnel after Hurricane Sandy. Photo Credit: MTA 2012 under Creative Commons Attributions License

7.3 Objective

For the Brooklyn Battery Tunnel, the costs of disruption are incurred by the MTA and the tunnel's 45,000 daily users. In the context of this research, an appropriate objective is to reduce the agency and user costs due to flooding and related disruptions. Agency costs comprise the lost toll revenues, and the costs to drain, clean, and repair all of the flooded parts of the tunnel. User costs could be considered as the amount that users are willing to pay to be able to use the tunnel. An estimate of user costs could be made by using the daily toll revenue.

7.4 Alternatives

There are a number of alternatives available to increase resilience to flooding. These alternatives function in different ways to reduce the probability, consequences, and recovery time associated with flood events. The effectiveness of these alternatives varies according to the nature of the alternative itself as well as the flood characteristics such as flood extent and duration. In this case study the alternatives are not all mutually exclusive; a combination of the alternatives can be used.

1. Permanent Pumps: MTA could install more pumps to remove water from the tunnel. This could reduce the extent of flooding and also reduce the duration of a disruption. MTA currently has three large sets of permanent pumps installed to drain the tunnel. These pumps were the first defense against Hurricane Sandy but eventually were submerged and failed.
2. Temporary Pumps: Contracts and plans to acquire more pumping capacity and use it more efficiently could reduce the length of a potential disruption. After Sandy, 15 pumps with capacities ranging from 1000 to 28000 gpm took nine days to remove the water from the Tunnels after Hurricane Sandy. If the average rate at which water is removed could be doubled, the disruption duration could be about four or five days shorter. This could be done by either adding more capacity, making plans to enable faster pump deployment or by planning and practice to make sure that the pumps that are available are used more efficiently and have less down time.
3. Flood gates: A flood gate could be added to the opening of the tunnel to prevent the entrance of water. The Midtown Tunnel in Norfolk Virginia has a large steel flood gate with seals around it is lowered in front of the tunnel entrance to prevent the entry of seawater (Toll Roads News 2012). A similar gate or other method to plug the tunnel entrance could prevent most of the water from entering the Brooklyn Battery Tunnel. However, even with a

floodgate, seepage from the ventilation system, utilities, and seals around the gate could still flood the tunnel during a major storm.

4. Waterproofing: Waterproofing components inside the tunnel would make it such that after the tunnel floods it could be immediately placed back into service after the water is removed and the tunnel is cleaned. Although the waterproofing of all components in the tunnel would likely be very costly, it may be possible to select components of the tunnel that are most at risk and could affordably be made more waterproof.
5. Seawalls: The seawalls protecting the greater southern Manhattan area could be improved such that seawater never even makes it close to the tunnel entrance.

Given the various alternatives, and the possibility to apply them simultaneously, the analysis of this case study can become quite complex. There are many questions that may be used to guide analysis. Because of this it is recommended to perform the analysis portion iteratively, answering questions as needed. In this example, two analyses are performed. The first analysis seeks to determine how much money can be justified to mitigate the tunnel’s flood risk. Once this is known, the second analysis seeks to broadly examine which alternatives are the most effective. Although only two analyses are done here, in practice it would be necessary to do a number of additional analyses to determine more precisely how to combine different mitigation strategies in an affordable way.

7.5 Analysis: Mitigation Investment Question

Before decision-makers start to sort out which alternatives will best meet their objectives, they may be interested in first determining how much they should be willing to spend on mitigation in the first place. The resilience approach described in Chapter Five can be used to solve this problem, as demonstrated in the following sections.

7.5.1 Purpose of Analysis:

Determine the maximum amount of money justifiable for mitigation.

7.5.2 Performance Requirement

The benefit cost ratio which considers only agency costs must be greater than 1.

$$Benefit\ Cost\ Ratio > 1$$

7.5.3 Decision Variables

The decision variable is the mitigation investment, which is the maximum amount justifiable for mitigation expenses.

7.5.4 Uncertainty Model

The uncertain parameters in this analysis are the probability of another flood event and the cost of that event. These are represented using a bounded uncertainty model as described in Section 5.4.3.1. Appendix B describes how these estimates were calculated.

Table 6. Parameters for a bounded uncertainty model

	Description	Lower Bound	Upper Bound
U_{cost}	Agency cost of a disruption	\$9 Million	\$18 Million
U_{Pflood}	Annual Probability of a Flood	0.01	0.10

7.5.5 System Model

The system model represents the benefit cost ratio. The benefits are the dollar value of the expected disruption agency costs that could be avoided through mitigation. The cost is the value of the mitigation investment.

$$Benefit/Cost\ Ratio = \frac{Avoided\ Disruption\ Costs}{Mitigation\ Investment}$$

The avoided disruption cost is the product of the cost of an average disruption multiplied by the annual probability of a disruption and the time period of analysis:

$$Avoided\ Disruption\ Costs = U_{cost} \cdot U_{Pflood} \cdot t$$

Where:

$U_{cost} =$ The cost average cost of a flood event

$U_{Pflood} =$ The annual probability of a flood event

$t = 50\ years$ The analysis time period

For simplification, the above equation neglects the time value of money and also the time varying nature of flood probability and disruption costs. In practice, the analysis should account for these. Time varying costs and flood probabilities and the time value of money could be considered using an equation such as the one below, which adds up the present value of the expected cost of disruption during each year.

$$Avoided\ Disruption\ Costs = \sum_{n=1}^{50} U_{cost,n} \cdot U_{Pflood,n} \cdot \frac{1}{(1+i)^n}$$

Where:

$n =$ The number of the current year

$U_{cost,n} =$ The cost average cost of a flood event in year n

$U_{Pflood,n} =$ The annual probability of a flood event in year n

$i =$ The interest rate

7.5.6 Results

Parameters from the uncertainty model are input into the system model to determine which values of the decision variable satisfy the performance requirements. For detailed calculations see Appendix B. One way of representing results is by simply providing bounds on the result:

> *When considering only agency costs, to achieve a benefit cost ratio of at least 1, the infrastructure investment must be less than between $4.5 and $90 million dollars.*

In this example, the uncertainties create a bounded result with a very large range. While, this large range of possibilities may seem like a non-useful result to the decision-maker, it communicates to the decision-maker the uncertainty involved in the decision. Since there is a great deal of uncertainty as to how likely another flood is, the justifiable mitigation investment is also highly uncertain. Although, the uncertainty may be difficult to reduce, other representations of the results can better help the decision maker understand the nature of the uncertainty.

More detailed information about the uncertainty can be found by performing a single variable info-gap analysis, or a sensitivity analysis on a single variable. Since only one variable is separated out, uncertainty for the rest of the variables can be represented by placing bounds on the graph. This result is pictured in Figure 9.

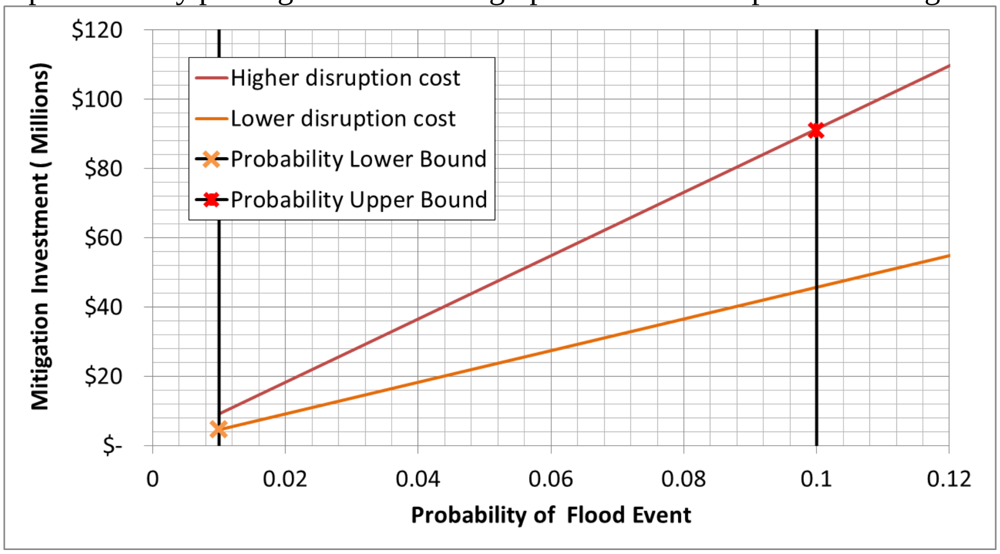

Figure 9. A range for justifiable mitigation investment amount as a function of uncertain probability of flood event.

In Figure 9 the bounds on the decision variable can be seen as a function of the uncertain probability of a flood event. The justifiable mitigation investment is highly dependent on the probability of more Sandy-like flood events. While this analysis procedure may not provide definitive results, it serves to better educate the decision-makers in the underlying uncertainties behind their decisions.

7.6 Analysis: Examining Alternatives

Once the analysis has been performed to estimate about how much spending on mitigation could be justified, further analysis is required to investigate mitigation options. This analysis demonstrates how the same approach described in chapter five may be used to inform the selection of an alternative.

7.6.1 Performance Requirement

The objectives for this case study are to reduce the agency and user costs of disruption over the analysis time period. However, since these costs can be difficult to calculate, it is possible to simplify the analysis by modeling the expected duration of all disruptions over the analysis time period. This simplification is made because both the user costs due to unavailability and the agency costs due to lost revenue and repair activities are all roughly linearly related to the length of disruption. So for this example, the performance requirement will be defined as:

The expected duration of all disruptions over 50 years shall be less than 4 days.

$$t_{expected50yr} < 4\ days$$

7.6.2 Decision Variables

The decision variables will represent the choices we can make regarding the various alternatives. For this example, the decision variables are not mutually exclusive options, some combination may be selected. Some of the decision variables are Boolean values while others are defined as a number. The decision variables are defined below:

D_{rateP} = The amount of permanent pumping capacity to add to the system (gpm)

D_{rateT} = The amount of temporary pumping capacity available after an event (gpm)$D_{floodgate}$ = 1 if a flood gate is installed, 0 if no flood gate is installed

$D_{waterproofing}$ = The number of recovery man-hours reduced by waterproofing work

$D_{seawall}$ = 1 if a seawall is installed, 0 if no seawall is installed

7.6.3 Uncertainty Model

For this problem, an info-gap uncertainty model is used. The uncertainty model was used for the probability of a flood event, seepage past a flood gate, storm duration, and effectiveness of improving local seawalls. The info-gap model was a simple model that incorporated the set of all possible values within a certain range of the best estimate. Best estimates and error values for the uncertain parameters are calculated in Appendix B and displayed in Table 7. The equation below representing the uncertainty model is a simple info-gap model as described in 4.3.2 and 5.4.3.3.

$$\mathcal{U}(\alpha, \tilde{u}) = \{u: |u_i - \widetilde{u_i}| \leq \alpha s_i\}$$

Table 7. Estimates and errors used for uncertain parameters in info-gap model.

	Parameter	**Estimate $\widetilde{u_i}$**	**Error s_i**
$U_{FG\ seep}$	Seepage past floodgate	2500 gpm	3000 gpm
U_{Pflood}	Annual Probability of Flood	0.02	0.001
$U_{duration}$	Storm Duration	8 hours	1 hour
U_{SWred}	Reduction of storm probability due to sea wall	0.1	0.02

7.6.4 System Model

The system model is the set of equations needed to represent the expected total length of disruptions over the course of an analysis time period of 50 years. This can be approximated as the product of a single disruption multiplied by the annual risk of a flood and the analysis time period of 50 years.

$$t_{expected50yr} = t_{disruption} \cdot U_{Pflood} \cdot 50\ years$$

Where:

$t_{expected50yr}$ = Expected duration of disruptions over a 50 year period

U_{Pflood} = Annual probability of a disruption

$t_{disruption}$ = The length of a single disruption event

The duration of a single disruption is calculated as the sum of the time it takes to pump out the water and the time it takes to clean and repair all of the tunnels components.

$$t_{disruption} = t_{pumping} + t_{work}$$

Where:

$t_{pumping}$ = The time required to pump the water out of the tunnels

t_{work} = The time required to clean the tunnel and fix broken parts

The time required to pump and clean and fix the tunnel can be further broken down. The time required to pump out all of the water is dependent on the total volume of the tunnel, the percent of the tunnel which has flooded, and the rate at which water can be pumped out.

$$t_{pumping} = \frac{Pct_{flooded} \cdot V_{tunnel}}{(D_{rateP} + D_{rateT})}$$

Where:

$Pct_{flooded}$ =The percentage of the tunnel that has flooded

V_{tunnel} = The volume of the tunnel

The time required to do the work to inspect, clean, and repair everything can also be broken down. The time required to inspect, clean and repair all of the parts of the tunnel depends on the extent to which the tunnel has flooded, the amount of time required to clean and repair everything in the tunnel, the amount of time saved due to waterproofing efforts, and the number of man-hours that can be put in each day to restore the tunnel to service. The following equation is used to estimate the amount of time required to repair the tunnel. The methods used to find the numbers used in the equation below are explained in Appendix B.

$$t_{work} = \frac{Pct_{flooded} \cdot t_{Total\,Work}}{LaborForce \cdot Work\ hours/day} \cdot \left(1 - D_{waterproofed}\right)$$

Where:

$t_{Total\,Work}$ = The number of man-hours required to do the work to inspect, clean and repair all parts

$D_{waterproofed}$ = Decision variable representing the percentage of recovery hours avoided due to waterproofing efforts.

The percentage of the tunnel which floods is modeled as a function of the water entry rate, pumping rate, storm duration, and tunnel volume. The flooded percentage of the tunnel is limited to a maximum value, assuming that future flood events will be like Sandy and only flood the 2/3 of the tunnel closest to the Manhattan portal.

$$Pct_{flooded} = \frac{\left(D_{rateP} - U_{FG\,seep}\right) U_{duration}}{V_{tunnel}} < 66.6\%$$

7.6.5 Results

For this analysis, decision variables were selected to look at each alternative individually, even though ultimately a combination of mitigation actions can be taken. The result can be graphed to show the performance of each alternative as a function of the horizon of uncertainty as shown in Figure 10.

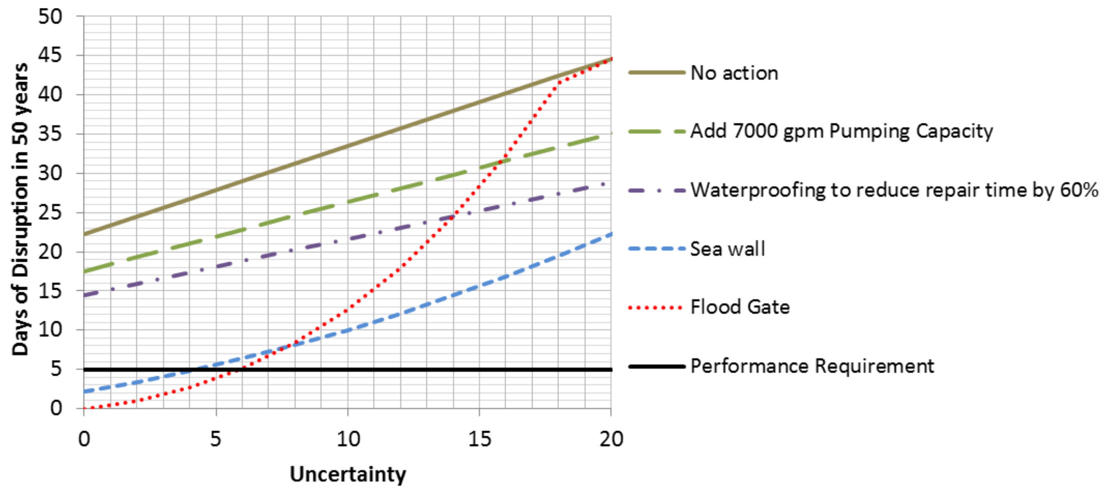

Figure 10. Performance of select alternatives given increasing uncertainty.

In Figure 10 the performance of each alternative is represented on the y-axis. The performance requirement for the total length of disruptions over 50 years is also represented. The x-axis represents varying amounts of uncertainty. If all the best-estimate values used in the uncertainty model turn out to be perfect, then the uncertainty would be 0. As the uncertainty increases, the total expected length of disruptions increases because the parameters in the uncertainty model exhibit more variation from the best estimate values.

Many conclusions can be drawn from this simple analysis. Leaving the tunnel as it is and taking no action shows the worst performance. The pumping and waterproofing strategies that focus on recovering from a flood faster both serve to transform the curve a few days lower. However they both fail to meet the performance requirement of having less than five days of disruption over 50 years. The alternatives that prevent flooding, the flood gate and the sea wall, are capable of meeting the performance requirement. If there were no uncertainty, the flood gate would guarantee no disruptions over the 50 year analysis period. However, as uncertainty increases the performance of the flood gate deteriorates as a larger amount of uncertainty allows more water to seep past the floodgate and fill the tunnel. Similarly, the sea wall can also meet the performance requirement up to a certain degree of uncertainty.

7.7 Further Analysis

Once these analyses have been performed, analysts and decision makers may wish to perform further analyses to better inform their decisions. There are many possible next steps for analysis. Analysts will probably want to further investigate the inputs to the analysis in section 7.6 to be a little more confident as to whether the sea wall or the flood gate would perform better. Analysts will likely need to begin to perform analysis to compare the construction and lifecycle costs of the most viable alternatives. Further analysis could also be done to experiment with different combinations of decision variables. Once workable strategies are chosen, it may be necessary to do more analysis to determine precisely what elevation to raise the seawalls or what pumping capacity to add. Although the analysis procedure has already been performed twice for this problem, it will often be necessary to repeat the procedure many times to develop all of the information needed to make a well-informed decision.

Chapter 8

CONCLUSIONS AND FUTURE WORK

The infrastructure which supports modern society is at risk of failure due to natural hazards, deterioration, accidents and terrorism. Infrastructure failures can cause death, injury, lost productivity, and other costs for infrastructure owners, operators, users and the broader community. While many tools exist to make decisions about infrastructure risks, it can be difficult to adequately consider the risks and uncertainty for a given problem. This thesis proposes an approach to inform project-level infrastructure decisions, while considering the risks and uncertainties involved. Although the approach has its limitations and can be difficult to implement, the approach has a variety of strengths and a wide range of applications.

8.1 Limitations

Due to the difficult nature of resilience and infrastructure systems, there are a number of limitations to the proposed approach. The approach is limited by its difficulty in accurately capturing resilience and its difficulty in capturing uncertainty and the true nature of the system in question.

8.1.1 Resilience

One limitation is that this method does not fully represent the true nature of resilience. While resilience is an easily understood concept, the measurement of resilience is somewhat ambiguous and can become very subjective and difficult to evaluate. For complex systems – like civil infrastructure systems – infrastructure resilience can be very difficult to measure, as the performance of a system is often much more than a single quantity.

This approach seeks to overcome the difficulty of resilience measurement by allowing the analyst to select whatever performance measures they view as suitable proxies for resilience. Depending on the problem at hand, different performance measures may be used, such as reliability, life cycle cost, risk, consequences of disruption and so on. Since the analyst is not measuring resilience directly, the results should help the decision maker pursue resilience, but will not be a perfect representation of true resilience. Although resilience cannot be directly represented, it can be pursued by using multiple metrics that together can be used as an adequate proxy for resilience. Ultimately the choice of metrics and the interpretation of those metrics in the context of resilience are up to the analyst and are subject to vary from the ideal of true resilience.

8.1.2 Uncertainty

Although the approach is intended to address uncertainties, there are limitations in the manner in which it addresses uncertainty. For some problems, there may be many uncertain parameters and/or parameters with an exceptionally large amount of uncertainty. These issues can undermine an analyst's ability to fully consider the uncertainty in a given problem.

For problems with many uncertain inputs, it can be difficult to meaningfully represent how the many uncertain inputs contribute to an uncertain output. For a bounded uncertainty model, these many variables are all lumped together to form a single bounds on the result. This may give the decision-maker a large range of uncertainty, while providing little insight into the many variables underlying the uncertainty. While using the info-gap method within this approach allows the analyst to consider many uncertain variables, it also has limitations. The info-gap method consolidates all of the input uncertainty into a single horizon of uncertainty, which is then used to determine the robustness. While this single measurement of uncertainty simplifies the analysis, it also makes it difficult for the decision maker to understand the meaning of the horizon of uncertainty or robustness values. Furthermore, in the process of consolidating multiple uncertain variables into a single horizon of uncertainty, the analyst makes assumptions as to how these uncertain variables may be related, and the relative extent to which each is uncertain. Given the unknown nature of uncertainty, it remains difficult to fully account for the unknown in any analysis. While this thesis attempts to overcome the problems imposed by uncertainty through the use of uncertainty models, large amounts of uncertainty on many parameters can still pose a problem for the analyst.

8.2 Challenges

Apart from limitations on the representation and solution for problems, there are also a number of challenges that can arise in the application of the approach to infrastructure resilience problems. These challenges include the open ended nature and complexity of many infrastructure problems.

8.2.1 Open Ended-ness

One of the benefits of the proposed approach is its flexibility in application to various circumstances and problems. However, this flexibility also creates a large degree of open ended-ness for the analyst, leaving them with limitless paths to analyze the same problem. While this approach provides a framework to guide more resilient decisions, in many cases the analyst may become stuck. Analysts may become stuck when they have difficulty finding the right tools to solve the problem. In other cases analysts may have a multitude of tools which can be used to solve the problem, but are left without knowing which tool is best or if the tools are equivalent. The open ended nature of the proposed approach can make the approach difficult to implement, as analysts will have to rely on their own judgment and ingenuity to apply appropriate tools to solve a given problem.

8.2.2 Complexity

The complexity of infrastructure systems and their associated risks can also be a challenge for analysts seeking to implement the proposed approach. Due to the complex nature of these systems and the many interactions amongst infrastructure, hazards and society, it can be very difficult to produce all of the information needed to properly perform an analysis. This complexity makes it difficult to choose tools, equations and parameters to model the problem. While the approach is geared towards uncertainties, the depth of complexity in these types of analysis can easily exceed an analyst's ability to model them accurately.

8.3 Strengths

The approach has a number of strengths. These strengths include its flexibility to include various tools, its ability to scale and its usefulness for a variety of different resilience questions.

A key strength of the approach is that it allows flexibility to utilize a wide range of existing tools to solve the problem. For example, life cycle cost analysis, benefit cost analysis, risk assessment and other tools can easily be applied as the system model in an analysis. Similarly, the approach allows for a variety of tools such as bounding, info-gap and others to model uncertainty. The approach is also flexible in that it allows analysts to determine what metrics they want to use as indicators of resilience.

Another strength of the approach is scalability. The proposed approach can scale from small problems to more complex problems. The approach can be applied using as simple or complex models as are necessary to solve the problem. The approach allows for problems to be solved mentally using simple qualitative models if possible. For slightly more involved problems, simple quantitative models may be applied using bounding to model uncertainty. For larger more complex problems, analysts can use whatever complex models are needed to accurately portray the nature of the system and its uncertainty. More complex analyses may incorporate a combination of risk assessment and life cycle cost tools to model the system along with a combination of bounding, probability theory, and info-gap theory to model uncertainties. The scalability of the approach is a key advantage because it facilitates the treatment of varied problems, and also allows analysts to iteratively perform analysis increasing in complexity as needed to solve a problem.

8.4 Applications

The approach described in this thesis has many possible applications for informing decisions to create more resilient infrastructure systems. The approach is useful for a range of scenarios involving project-level infrastructure decisions. The method can be used to answer a variety of common questions pertaining to various infrastructure risks:

- What magnitude of event should be used as the design event for a given hazard?

- What is the maximum investment that would be rational to mitigate a given hazard?
- Which mitigation alternative(s) should be selected?
- How should a variety of mitigation techniques be balanced?

All of these questions and more can be answered by applying the described approach. The method is sufficiently general such that it may be used in various infrastructure sectors such as transportation, energy and water. The approach is also applicable to various hazards, including flooding, wind, blast, seismic and others. The approach is particularly useful for situations in which there exists significant uncertainty, such as for climate change and sea level rise concerns.

8.5 Future Work

There is a great deal of work that could be done to improve the proposed approach for resilience decision-making.

Since this approach relies on the analyst's judgment in finding proxy measures resilience, it would be beneficial if there were more complete guidance on how to use proxy measures to estimate resilience. Such information might include ideas for proxy measures on resilience for different types of systems and hazards. Guidance could also discuss the use of multiple proxy measures and how they should be used together to better achieve resilience.

Another possible area of improvement would be the development of better ways to model, analyze, represent and communicate uncertainty. Although a variety of tools already exist to perform this function, situations with many highly uncertain variables are still difficult to represent properly.

8.6 Conclusions

Disasters such as Hurricane Sandy and the Japan Tohuku Earthquake, Tsunami and Nuclear Disaster illustrate the effects of infrastructure system failure on communities. Although resilience is an increasingly employed organizing principle to overcome these challenges, it can be difficult to implement. In particular, making more resilient civil infrastructure systems in a cost effective manner can be difficult due to the ambiguity of resilience and the complexity and uncertainties involved in infrastructure risk. This thesis has laid out an approach that can be used to direct analysis to better inform infrastructure risks. Although this approach provides a guide to follow, there can arise many challenges in making decisions for resilient infrastructure. These challenges arise from the uncertainty and complexity involved in the interactions amongst hazards, infrastructure, and society.

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Appendix A

PRIME HOOK ROAD CASE STUDY CALCULATIONS

This appendix contains more in-depth calculations and numbers used for the quantitative analysis of Prime Hook Road.

A.1 Uncertainty Model

Although there are many parameters with uncertainty, for simplicity the uncertainty model only included one variable, that being sea-level rise.

A.2 System Model

The system model includes a number of constants that describe the consequences of varying flood events. Information on the costs of flood events and road closure durations were derived from data sources about Prime Hook Road during previous flood events. Data comes from NOAA's tides and currents tide data, DelDOT's database of traffic alerts which includes notifications of road flooding, and DelDOT's Maximo asset management database which tracks maintenance and repair costs. A summary of the major storms that have affected Prime Hook Road from 2009-2012 and the associated costs and road closures are presented in Table 8. The data from this table was used to make estimates for the cost of failure and the duration of disruption parameters which are explained in sections A.2.1 and A.2.2.

Table 8. Summary of data describing flood events and their consequences for Prime Hook Road.

	Date	HAZARD Tide (ft above MSL) Highest	DAMAGE	REPAIR COST Cost	Action	CLOSURE DURATION Days
	9/27/2010	3.7	Potholes?	$ 2,304	Pothole Repair	
	8/18/2010	4.07	Debris	$ 110	Debris Cleanup	
	12/26/2012	4.37	None	$ -	None	1
	3/3/2010	4.42	Shoulders	$ 6,003	Shoulder work	
	3/13/2010	4.66	Potholes	$ 3,102	Pothole Repair	
	6/4/2012	5.07	Shoulders	$ 3,324	Shoulder work	1
	10/28/2011	5.45	Moderate	$ 19,938	Repair wash-out	1
Irene	8/27/2011	5.74	Major	$ 52,269	Major Rebuild	5
Sandy	10/28/2012	6.46	Extreme	$ 126,384	Total Rebuild	9

A.2.1 The cost of failure i for alternative q

This parameter describes the cost of failure for a given alternative (q) and flood event (i). The values used in this analysis are found in the table below. These costs reflect an estimate of the direct agency costs required to repair the roadway after a major flood event.

$C_{i,q} =$ The cost of failure i for alternative q

Table 9. Values for $C_{i,q}$ the cost of failure for flood event i, and alternative, q.

Event, i		Decision, q As Usual	Elevate	Bridge	Alternate Path
Small event	0	$4,500	$4,500	$0	$0
	1	$20,000	$20,000	$0	$0
	2	$50,000	$50,000	$0	$0
Major Event	3	$125,000	$125,000	$5,000	$0

A.2.2 The Duration of Road Closure for Flood Event, i and Alternative q

This parameter describes the expected duration of road closure due to a given flood event (i) for a given alternative (q). Flood events are classified from 0 to 3, with i=0 being a minor event and i=3 being a major event. The values used in this analysis are found in the table below. These numbers reflect an estimate of the number of days of road closures associated with each combination of flood event and alternative. For the As Usual, Elevate and Alternate Path alternatives the duration of closure for each category of event are the same. The difference between these alternatives is that to cause the same flood event, a higher tide level is required for the Elevate and Alternate Path alternatives.

$N_{i,q} =$ The estimated road closure duration for event, i and alternative, q

Table 10. Values for $N_{i,q}$ the estimated road closure duration for flood event i, and alternative, q.

Event, i		Decision, q			
		As Usual	Elevate	Bridge	Alternate Path
Small event	0	0	0	0	0
	1	1	1	0	1
	2	5	5	0	5
Major Event	3	9	9	0	9

A.2.3 Probability of a given event

The probability of a given event depends on the elevation of the storm surge and the some threshold at which that alternative will flood. The thresholds vary from alternative to alternative. For example, the threshold for a small event for the "As usual" alternative is 4.42 ft. This elevation is associated with the sea level required to produce a small flood that would require road maintenance and repair, and closures as defined in the previous tables. For the elevate alternative, the thresholds are all increased by 2 ft. This assumes that the road will be elevated 2 ft and that to produce the same amount of damage a storm will have to produce a surge two feet higher. The alternate path uses thresholds 1 foot higher than those for the as usual alternative, because the existing alternative path is situated only about a foot higher than Prime Hook Road.

Table 11. Sea level elevation thresholds to produce different events for each alternative.

Event, i		**Decision, q**			
		As Usual	Elevate	Bridge	Alternate Path
Small event	0	4.42 ft	6.42 ft	0	5.42 ft
	1	5.45 ft	7.45 ft	0	6.45 ft
	2	5.74 ft	5.74 ft	0	6.74 ft
Major Event	3	6.46 ft	8.46 ft	7 ft	7.46 ft

These thresholds can be used to calculate the risk associated with each event for a given alternative. The risk of each event is calculated based on the extremes of 22 years of monthly tide data taken by NOAA’s Tide monitoring station at Lewes, Delaware. To calculate the risk of flooding, given increasing sea level rise the 22 years of monthly tide data was offset by the amount of sea-level rise to model possible risk for a higher sea level. Due to the lack of data and resources to adequately analyze sea level rise, this has been done for simplification. It is recognized that sea-level rise may have different impacts on tides levels and storm surges that are not fully modeled by simply offsetting historical data by a given amount.

Once the probabilities and consequences can be calculated for any given storm event and alternative, it is possible to calculate the results presented in section 6.4.4 using the equations presented in section 6.4.3 for the system model.

Appendix B

BROOKLYN-BATTERY TUNNEL CASE STUDY CALCULATIONS

B.1 Analysis: Mitigation Investment Question

B.1.1 Uncertainty Model: Agency Cost of a Single Disruption

This parameter is the cost to MTA of a single flood-caused disruption**.** This calculation assumes that all disruptions would be similar to that caused by Hurricane Sandy. Calculations for a lower and upper bound for this parameter are below:

$$U_{costLB} = Cost_{labor} + Cost_{LostTolls}$$

$N_{workers} := 200$ Number of employees at Tunnel (Toll Roads News 2011)

$t_{overtime} := 44\frac{hr}{week}$ Assume that workers are working 12hr days, 7 days a week (Toll Roads News 2012)

$Wage := \frac{70USD}{man \cdot hr}$

$t_{duration} := 22day$ (Toll Road News 2012)

$$Cost_{overtime} := Wage \cdot t_{overtime} \cdot N_{workers} \cdot t_{duration} = 1.936 \times 10^{6} \cdot USD$$

$$Cost_{regulartime} := Wage \cdot 40\frac{hr}{week} \cdot N_{workers} \cdot t_{duration} = 1.76 \times 10^{6} \cdot USD \qquad veh := 1$$

$$Cost_{labor} := Cost_{overtime} + Cost_{regulartime} = 3.696 \times 10^{6} \cdot USD$$

$AADT := 45000\frac{veh}{day}$ Average annual daily traffic in 2011 (Toll Roads News 2012)

$AverageToll := 5.33\frac{USD}{veh}$ Average Toll in 2011 (Toll Roads News 2012)

$$AADT \cdot AverageToll = 2.398 \times 10^{5} \cdot \frac{USD}{day}$$

$$Cost_{LostTolls} := AADT \cdot AverageToll \cdot t_{duration} = 5.277 \times 10^{6} \cdot USD$$

$$U_{costLB} := Cost_{labor} + Cost_{LostTolls}$$

$$U_{costUB} := 2U_{costLB}$$

$\boxed{U_{costLB} = 9 \times 10^{6} \cdot USD}$ Lower bound of agency cost for a single Sandy-like disruption

$\boxed{U_{costUB} = 18 \times 10^{6} \cdot USD}$ Upper bound of agency cost for a single Sandy-like disruption

B.1.2 Uncertainty Model: Probability of Sandy-Like Disruption

Hurricane Sandy was the only storm event in recorded history to cause such a large storm surge in the New York region Because of this, there is a great deal of uncertainty about how frequently such a storm will occur in the future. This uncertainty is further increased when considering climate change and sea level rise.

One of the simplest ways this could be estimated is by calculating the recurrence interval based on how often such an event has occurred historically. When looking at the last 100 years only one storm (Sandy itself) caused flooding that would flood the Brooklyn Battery Tunnel. So the chances could be 1/100. If we believe that the last 100 years are a poor indicator of the future, we could make the same calculation using only the last 10 years of data. Since there was one such event in the last 10 years, then looking only at the last ten years, we could say there is a 1/10 annual chance of Hurricane-Sandy like flooding at the tunnel.

$U_{PfloodLB} := \frac{1}{100yr} = 0.01 \cdot \frac{1}{yr}$ Lower bound on probability of Sandy-like flood.

$U_{PfloodUB} := \frac{1}{10yr} = 0.1 \cdot \frac{1}{yr}$ Upper bound on probability of Sandy-like flood.

B.1.3 System Model Calculations

$BCR > 1$

$$BCR = \frac{Avoided\_Disruption\_Costs}{Mitigation\_Investment}$$

$t_{analysis} := 50yr$

$Avoided\_Disruption\_CostsUB := t_{analysis} U_{PfloodUB} \cdot U_{costUB} = 90 \times 10^6 \cdot USD$

$Avoided\_Disruption\_CostsLB := t_{analysis} \cdot U_{PfloodLB} \cdot U_{costLB} = 4.5 \times 10^6 \cdot USD$

$$\boxed{Mitigation\_CostsUB := \frac{Avoided\_Disruption\_CostsUB}{BCR} = 90 \times 10^6 \cdot USD}$$

$$\boxed{Mitigation\_CostsLB := \frac{Avoided\_Disruption\_CostsLB}{BCR} = 4.5 \times 10^6 \cdot USD}$$

B.2 Analysis: Examining Alternatives

B.2.1 Decision Variables

Although there are many possible ways to combine these decision variables, this analysis focused on only 5 alternatives. The values used for each of the decision variables for the five alternatives are shown in Table 12. Further analysis should be done to determine how decision-makers may want to combine decisions. All of the decisions include some amount of pumping capacity, as the tunnel already has some capacity. The values used for baseline pumping capacity are estimated based on information from articles about tunnel flooding (Toll Roads News 2012).

Table 12 Decision Variables for Alternatives Considered in this Analysis

	Decision Variables				
Alternative	$D_{floodgate}$ Y/N	D_{rateP} gpm	D_{rateT} gpm	$D_{waterproofing}$ hrs	$D_{seawall}$ Y/N
As usual	0	2500	4000	0	0
Floodgates	1	2500	4000	0	0
Add Pumps	0	7500	6000	0	0
Waterproofing	0	2500	4000	60%	0
Seawall	0	2500	4000	0	1

B.2.2 Uncertainty Model

Values and estimates used for the uncertainty model are shown in Table 13. Seawall probability reduction refers to the extent to which the seawall reduces the probability of a flood reaching the tunnel portal. It was assumed that the seawall makes a Sandy-like event 1/10 as likely as it was previously. The probability of a Hurricane Sandy like flood event was assumed to be 1/50 or 0.02. The seepage was estimated based on seepage in the Elizabeth River Tunnel in Virginia (Toll Roads News 2012).

Table 13. Values used for uncertainty model.

	Uncertainty			
	Seawall Probability reduction	Probability of flood	Seepage (gpm)	Storm Duration (hr)
	$U_{sw\ red}$	**U_{pflood}**	**$U_{FG\ seep}$** gpm	**$U_{duration}$** hr
Estimate	0.1	0.02	2500	8
Error	0.02	0.001	3000	1

B.2.3 System Model

The system model uses a spreadsheet to model the effects that increasing uncertainty had on the total duration of disruptions over 50 years for each alternative. The spreadsheet is shown in Table 14. The equations used within the spreadsheet are explained in section 7.5.5

Table 14. System model calculations

	Decsion Variables					Uncertainty						Results			
Alternative	$D_{floodgate}$	D_{rateP}	D_{rateT}	$D_{waterproofing}$	$D_{seawall}$	α	$U_{sw\ red}$	U_{pflood}	$U_{FG\ seep}$	$U_{FG\ seep}$	$U_{duration}$	PctFlooded	$t_{pumping}$	t_{work}	$t_{disruption50}$
	Y/N	gpm	gpm	hrs	Y/N				gpm	gpm	hr	%	hrs	days	days
As usual	0	2500	4000	0	0	0	NA	0.02	200000	2500	8	66.67%	9.2	13.1	22.3
As usual	0	2500	4000	0	0	1	NA	0.021	210000	5500	9	66.67%	9.2	13.1	23.4
As usual	0	2500	4000	0	0	2	NA	0.022	220000	8500	10	66.67%	9.2	13.1	24.6
As usual	0	2500	4000	0	0	3	NA	0.023	230000	11500	11	66.67%	9.2	13.1	25.7
As usual	0	2500	4000	0	0	19	NA	0.039	390000	59500	27	66.67%	9.2	13.1	43.5
As usual	0	2500	4000	0	0	20	NA	0.04	400000	62500	28	66.67%	9.2	13.1	44.6
Floodgates	1	2500	4000	0	0	0	NA	0.02	0	2500	8	0.00%	0.0	0.0	0.0
Floodgates	1	2500	4000	0	0	1	NA	0.021	0	5500	9	1.26%	0.2	0.2	0.4
Floodgates	1	2500	4000	0	0	2	NA	0.022	0	8500	10	2.79%	0.4	0.5	1.0
Floodgates	1	2500	4000	0	0	3	NA	0.023	0	11500	11	4.60%	0.6	0.9	1.8
Floodgates	1	2500	4000	0	0	20	NA	0.04	0	62500	28	66.67%	9.2	13.1	44.6
Add Pumps	0	7500	6000	0	0	0	NA	0.02	200000	2500	8	66.67%	4.4	13.1	17.6
Add Pumps	0	7500	6000	0	0	1	NA	0.021	210000	5500	9	66.67%	4.4	13.1	18.4
Add Pumps	0	7500	6000	0	0	2	NA	0.022	220000	8500	10	66.67%	4.4	13.1	19.3
Add Pumps	0	7500	6000	0	0	3	NA	0.023	230000	11500	11	66.67%	4.4	13.1	20.2
Add Pumps	0	7500	6000	0	0	20	NA	0.04	400000	62500	28	66.67%	4.4	13.1	35.1
Waterproofing	0	2500	4000	60%	0	0	NA	0.02	200000	2500	8	66.67%	9.2	5.3	14.4
Waterproofing	0	2500	4000	60%	0	1	NA	0.021	210000	5500	9	66.67%	9.2	5.3	15.2
Waterproofing	0	2500	4000	60%	0	2	NA	0.022	220000	8500	10	66.67%	9.2	5.3	15.9
Waterproofing	0	2500	4000	60%	0	3	NA	0.023	230000	11500	11	66.67%	9.2	5.3	16.6
Waterproofing	0	2500	4000	60%	0	20	NA	0.04	400000	62500	28	66.67%	9.2	5.3	28.9
Seawall	0	2500	4000	0	1	0	0.1	0.02	200000	2500	8	66.67%	9.2	13.1	22.3
Seawall	0	2500	4000	0	1	1	0.12	0.021	210000	5500	9	66.67%	9.2	13.1	23.4
Seawall	0	2500	4000	0	1	2	0.14	0.022	220000	8500	10	66.67%	9.2	13.1	24.6