ABSTRACT

PIPER, BRIAN E. A Decision Framework for Improving Resilience of Civil Infrastructure Systems Considering Effects of Natural Disasters. (Under the direction of Dr. Ranji S. Ranjithan, Dr. E. Downey Brill and Dr. John Baugh).

The effects of natural disasters in civil infrastructure systems can be substantial. Damage to infrastructure components, such as roads, bridges, levees, dams, buildings and houses, causes economic loss and disrupts critical lifelines. Continued coastal development requires building more resilient infrastructure systems capable of withstanding or recovering from damaging effects caused by natural hazards. This thesis addresses the need for a framework capable of identifying infrastructure investment decisions that can improve system resilience and reduce system-wide risk from natural disasters.

A brief background is given of the concept of interdependent infrastructure components and the importance of including interdependencies in integrated modeling of infrastructure systems. Different categories of past modeling efforts are reviewed, with categories defined by both model structure and abilities, especially the abilities to change system behavior, prescribe decisions, and incorporate uncertainty in analysis.

One of the issues with current infrastructure modeling is a deficiency in defining meaningful and varied system performance functions. Different types of quantitative performance measures (or metrics) for infrastructure systems are considered. Metrics are developed for characterizing serviceability (the potential for an infrastructure to fulfill lifeline needs), property damage, travel time, and cost of upgrades and retrofits. These metrics are intended to evaluate the collective performance of the components of the system, and to prioritize and determine the effect of decisions such as upgrades and retrofits.

Models are developed that are realizations of different scenarios, each based on particular combinations of the infrastructure system and its traits of interest, especially the interdependencies and interrelationships. The range of models developed begins with systems that have a protective infrastructure, such as a levee, and flexibility allows the modeling framework to be extended to include numerous other situations. The definitions of the decision variables and the model expressions allow the formulation of generic mathematical optimization models that could be solved using mathematical programming techniques dependent on input data. An illustrative example demonstrates the validity of the concepts.

A Decision Framework for Improving Resilience of Civil Infrastructure Systems Considering Effects of Natural Disasters

by

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DEDICATION

Dedicated to Maria and my parents, Todd and Barbara.

BIOGRAPHY

Brian Piper is from Mankato, Minnesota, where he graduated from St. Clair High School, developing a taste for all things casserole. He completed his undergraduate work at Oberlin College, in Ohio. While at Oberlin, he finished the complementary majors of theater and mathematics, assuring himself a long and lucrative career. When not studying, he enjoys walking through parks with his dog and wife and performing in Raleigh's Village Idiots, a local improv comedy troupe.

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Chapter 1

Introduction

> The consequences of any engineering decisions need to be considered on a system basis; there is a long history of engineering failures based on unintended consequences.

- Seed et al. (2006)

The devastation of New Orleans after Hurricane Katrina dramatically displayed the pressing need for systems analysis of critical civil infrastructure. Analysis of individual failures, while important, should be appropriately incorporated into systems analysis. Making better engineering decisions to protect critical lifelines during a natural disaster is an absolutely essential challenge to overcome, which can only be met through considering the collective and interdependent performance of individual components of civil infrastructure. This thesis is intended to be a contribution to civil infrastructure system models capable of assisting in making decisions that improve the resilience of the infrastructure by reducing system risk.

First, some of the history and concepts associated with critical infrastructure and interdependencies are reviewed in Section 2.1. Next, in Section 2.2, prior modeling efforts are analyzed and classified according to model abilities. Also, the structures of past models are considered, with a discussion on the limitations and advantages inherent the various model mechanics.

A generic decision framework is developed in Section 3.1, capable of handling different measurements of system performance, or metrics. These metrics are described in Section 3.1 as well, and they characterize serviceability (the potential for an infrastructure to fulfill lifeline needs), property damage, travel time, and cost of decisions made for system components. The metrics developed quantify the collective performance of infrastructure components and measure the effects different decisions have on system risk.

Modeling instances of the decision framework begin with viewing aggregated components of infrastructure in Section 3.1 and continue with consideration of subsystems of individual components of the infrastructure in Section 3.2. These latter instances consider how infrastructure components are interdependent without considering the relationships among components of the same infrastructure that affect system performance. Extended model instances in Section 3.3 consider how the relationships among components that affect the system performance.

The issues with extending the proposed framework to additional situations are explored in Chapter 4. Finally, in Chapter 5, an illustrative example of a model instance in Section 3.2 is solved using a linear programming realization of the scenario. This example demonstrates that the framework is capable of identifying decisions for infrastructure components according to a metric intended to quantify system risk.

Chapter 2

Background

2.1 Civil Infrastructure System Components and Their Interdependencies

The President's Commission on Critical Infrastructure Protection (PCCIP) was established in July 1996 to recommend a strategy for protecting the nation's infrastructure from physical and cyber threats. Their report concluded that "after fifteen months of evaluating the infrastructures, assessing their vulnerabilities, and deliberating assurance alternatives, our fundamental conclusion is that we have to think differently about infrastructure protection today and in the future" (PCCIP, 1997). Focusing on eight infrastructures in five sectors, the commission analyzed the infrastructure vulnerabilities and established organizational guidelines for public-private partnerships to improve these infrastructures. The eight infrastructures on which they focused are:

- Information and Communications
- Electrical Power Systems
- Gas and Oil Production, Storage, and Transportation
- Transportation
- Banking and Finance
- Water Supply Systems

- Emergency Services
- Government Services

These eight infrastructures have been deemed absolutely essential to the security and economic prosperity of the United States of America. Over the years, increased interactions among infrastructures have raised their risk exposure, making the study and analysis for increasing the resilience of these systems of paramount importance. The increase of infrastructure interactions requires introducing the concept of **Interdependence**, when the state of an infrastructure is dependent, through complicated linkages, on the state of other infrastructures (Rinaldi et al., 2001). Various classification schemes exist for defining possible types of interdependencies (Rinaldi et al., 2001; Lee et al., 2007); below is the one suggested by Rinaldi.

Physical These dependencies correspond to the view that each infrastructure provides services or goods that are demanded and consumed by another. The electricity needed for a water treatment plant is an example.

Geographic This dependency connects infrastructures by their relative position to one another. Examples can cover instances such as an important bridge for shipping that is adjacent to a sports stadium, both are possible terrorist targets. An attack on either could cause damage to the other because of their proximity.

Cyber When the state of critical infrastructure is dependent on information from another infrastructure, this is called a cyber interdependency. Modern railway systems that require computers to control the flow of trains is an example of a cyber interdependency.

Logical This category contains "other" interdependencies, such as the effects of policies and deregulation, human behavioral factors, etc., that may relate infrastructures.

In some instances infrastructures can have more than one type of interdependency. This is especially true for a transportation network, for instance, where emergency medical services may need to cross a bridge that has been damaged by a storm. However, before crossing the bridge, a repair crew will have to fix the bridge to an operable level, which is an example of a logical interdependency. Additionally, the necessity for both medical personnel to use the bridge provides an example of a physical interdependency.

Classifying the type of interdependency only begins to appropriately characterize a dimension of the infrastructure interdependencies. Many other dimensions exist and require characterization, but further discussion is outside the scope of this thesis. More information is provided by Rinaldi et al. (2001).

The ultimate goal of analyzing these systems is to reduce the risk caused by hazards. The risk of an event is generally defined as the product of the likelihood of the event and the consequences of that event; that is, it is the expected consequences of an event (Moselhi et al., 2005). We can write that risk as:

$$R = P \times C \tag{2.1}$$

where R stands for risk, P for the probability of an event, and C for the consequences from that event. This definition is useful in the analysis of infrastructure systems. In the case where the event is a willful action, this definition of risk might require modification (Rinaldi, 2004). However variations are defined, reducing the risk can be accomplished by making decisions that can reduce the likelihood of an event or reduce the consequences of an event.

2.2 Prior Models

Before developing new models for reducing risk in civil infrastructure systems, it was important to survey other efforts. Model capabilities, purpose, and limitations were analyzed to understand where new modeling efforts could contribute. The various surveys on this subject make it possible to refrain from discussing many details here. See Rinaldi (2004), Pederson et al. (2006), and Rigole and Deconinck (2006) for more information.

2.2.1 Ability Categories

Many different modeling approaches with different abilities have been applied to infrastructure systems, and the following categories are used to describe their abilities. First, the decision support capability of the model can be classified. A distinction is made between optimization models that are prescriptive and capable of recommending a course of action and simulation models that are only descriptive of system behavior.

Simulation Descriptive model of the systems. No decision is made according to a rigorous mathematical method.

Optimization Prescriptive model that may simulate, but also has a formal mathematical method for prescribing decisions.

A simulation model is capable of elementary analysis of system behavior, but optimization models have the advantage of formal metrics or formal search strategies to back the recommendation of various alternatives. For the purposes of this review, an optimization model needs a function, or class of functions, that quantitatively measures system performance, which will be called a metric in this thesis. Additionally, this metric needs to be explicitly used to provide a comparison of alternative decisions.

Models can also be classified by the type of system behavioral analysis supported. The categories are:

Strategic This model analyzes how the design of the system can affect system behavior.

Operations Analyzes system behavior in current system design, frequently considering the steady-state or return to steady-state from a disruption.

If modeling goals are to improve resilience and protect critical lifelines, then a strategic model is an absolutely essential component, because the current operation of the system may not be sufficient to achieve these goals. Also, note that a strategic model is not necessarily an optimization model, which requires formal mathematical functions for measuring system performance. Models like the Leontief Input-Output Inoperability Model (Haimes and Jiang, 2001) are models that simulate and consider how the system behavior can be changed, without having a formal metric explicitly capable of searching for alternative decisions.

The key difference between the strategic and operations abilities is that an operations model assumes that system components and structure will be unchanged, but a strategic model is capable of accepting dynamic system design and behavior. Many models that consider restoration of the "Vital Human Services" sector after a disaster are operations models, but measure the deployment of resources in a mathematically formal setting capable of optimization.

Finally, a distinction is made between models that are **Deterministic** and those that are **Probabilistic**, which incorporate uncertainties. As risk to civil infrastructure is based on likelihood of an event and consequences, which can both be uncertain, infrastructure models including uncertainty are preferred.

2.2.2 Model Structure

Models are not only classified by the categories above, but also by the mechanics and structure of the models. The majority of infrastructure interdependency models can be classified as three broad types.

Networks

These models view infrastructure systems as providing services that are in turn consumed by other systems. For instance, a functioning water supply system is necessary for a population, but it is dependent on the electrical system being able to provide enough power at certain points. These models are frequently able to provide "what-if" analysis by considering potential infrastructure failures and cascading effects across the system.

A variant of the view of production and consumption needs is the **connectiv-**

ity network model. Here, while the services that one infrastructure provides another are considered, only the possibility of providing any services from one system to another is of concern, as opposed to meeting some specific level of demand.

Lee et al. (2004) provide an example of a connectivity model with simulation, operations, and deterministic capabilities. Their proposed model compares alternative system designs. From a specific component in a system, an algorithm searches backward on a dependency graph to determine the essential links and components for an operable system. The dependencies determined can then be compared against the dependencies of alternative designs to determine overall vulnerability. While simple, it is nonetheless closer to a strategic model than the *Fast Analysis Infrastructure Tool* (FAIT) (McLaren and Brown, 2005) from Sandia National Laboratory, which models cascading damage, considering only an operations viewpoint without explicit support for analyzing alternatives.

While these connectivity network models are helpful for determining potential cascading failures, they should not be used in isolation. As input to another decision model, they can provide valuable information about competing infrastructure designs. In the end, the simplicity of the analysis make these models more suited as input to larger frameworks.

Network models consider mainly the capacity as well as connectivity of interdependent infrastructure systems. Many are optimization or strategic models. There are mixed integer/linear programming models that solve network flow problems to restore services after a disruption to the infrastructure system (Lee et al., 2007). Another interesting optimization and strategic model considers investments to enable faster restoration of supply lines (Nozick et al., 2005). These models can only perform a "what-if" risk analysis and model the return to equilibrium (or restoration of services). They focus on consequences, and how consequences, and therefore risk, can be reduced.

Drawbacks exist for this model class. When considering only quantities of demand and supply, certain characteristics of the system might be lost. In the case of a protective structure, such as a levee or flood wall, it is difficult to quantify the protection demanded by other infrastructures. Moreover, if the structure fails, then it may not be sufficient to consider the restoration of protection as an unpenalized outcome. While there could be a time-related penalty, the return to equilibrium may not be the best option. Also, when considering the time period to return to equilibrium, consequences that extend beyond the recovery time may be unintentionally omitted. Finally, an outcome representing a return to an unsafe equilibrium could result and should be recognized.

These models tend to not consider what failures should be evaluated. While other models, like the connectivity models, could help determine which failures should be considered, there is no entirely clear procedure for combining connectivity and supply-demand models. Suppose that a decision was made to analyze the component failures with the greatest probability of occurrence. In the case of a natural hazard, this is not necessarily a reasonable way to compute risk. Even failures with a low likelihood should be considered if the consequences are sufficiently large. The devastation from Hurricane Katrina is proof of that.

Input-Output Inoperability

Based on the work by Wassily Leontief, Input-Output Inoperability (IIO) models are similar in some respects to network models, because infrastructures are connected to one another via resources and risks. IIO models consider as output the **risk of inoperability** of a system of interdependent infrastructures (Haimes and Jiang, 2001). While the original Leontief economic model uses monetary units, the adaptation of the model to critical infrastructure uses units of risk of inoperability. Instead of using resources to produce goods, the model uses resources to manage inoperability. These models can be considered strategic simulations because while they only describe system reactions, possible changes to the system reaction to disruption are considered.

One of the issues with this approach is the need to provide a single number for the probability that the failure of one infrastructure affects another. Assuming it is possible to obtain these failure probabilities, these models can provide a high-level assessment of the resilience of civil infrastructure systems given the increase of inoperability level of a particular infrastructure. IIO models can be used to analyze the cascading effects across the entire infrastructure system and determine a new equilibrium point after an infrastructure reaches a particular level of inoperability (Haimes et al., 2005b). Additionally, these models can evaluate how the operability of the infrastructure system evolves toward an equilibrium and the effects of capital investment on damage mitigation. Not unexpectedly, it is necessary to provide reasonable inputs to model the effects of investment actions. On a system-wide level, providing these inputs may be difficult to do, whereas at a component level, defining the effects of capital investment action might be easier.

There are other limitations to this approach. There are no systematic search capabilities to identify cost-effective allocation decisions, merely comparisons of reduction in economic loss and costs of mitigation investments (Haimes et al., 2005b). Determining the likelihood of external pressures contributing to inoperability in a particular system is poorly defined, and the nature of the model makes it better suited to targeted and concentrated impacts rather than unfocused damage that frequently accompanies natural hazards such as hurricanes (Haimes et al., 2005a). While determining the effects of these targeted impacts is important, models capable of wide-scale, untargeted damage are necessary for natural hazards.

Agent-Based

Agent-based models encompass both simulations and game theory models, because at times the similarities in approach have caused the former to be used to solve the latter. These model types are frequently employed because each infrastructure system is created as a self-contained module in the entire system of critical infrastructures. This modularity makes consideration of different infrastructures as simple as the addition or substitution of individual modules. A sub-category of these modeling efforts can be called **Simple Systems**, so named not because of any reference to the level of sophistication of these models, but in reference to their limited scope. The simple systems are included here because they often have the viewpoint of a single agent and could be placed in a larger agent-based simulation.

Agent-based simulations fall into a class of models that generates a great deal of excitement in the literature on interdependent infrastructure modeling (Rinaldi, 2004; Rigole and Deconinck, 2006; Macal and North, 2005; Glass et al., 2006). The basic idea is that each agent behaves according to its own rules of engagement and interacts with other agents to fulfill its goals in response to casual inputs to the system. Each agent has an interface for input and another for output. Another reason for the popularity of these models is that they effectively capture the real-world scenario where much of the critical infrastructures are owned by private entities who are possibly unwilling to share information and definitely unwilling to cede control to a central authority. In terms of protecting infrastructure, it may be necessary to know, however, the actions of other sectors to optimally choose decisions based on their effects.

A compromise between viewing allocations as the domain of a central authority or as decisions made at the level of multiple individual entities occurs in a model of a Stackelberg game using agent-based simulation presented by Peeta et al. (2005). Three infrastructures (automobiles, urban freight, and data) are composed as dynamic agents. Network flow equilibria for individual infrastructures are established, while a "super-authority" allocates budgets for investments. The complexity of this problem when scaled to a real-world situation necessitated solution by agent-based simulation, instead of exact mathematical programming solution methods. There are definitely many advantages to using this technique, but also some drawbacks. The system has to start at disequilibrium and establish an equilibrium over several iterations. It is possible within a framework like this to add disruptions that occur over time, but this capability is not explicitly developed. Also, typically the decisions are for operational resilience and restorations of services, and strategic mitigation is not necessarily a direct criterion.

Simple systems include many efforts that are submodels in a larger infrastructure modeling package. One example is the Urban Infrastructure Suite (UIS) from Los Alamos National Laboratory (Barrett et al., 2004). Coupled in this package are TransSims, Water Infrastructure Simulation Environment (WISE) (McPherson and Burian, 2005), Interdependent Energy Infrastructure Simulation System (IEISS), and models for other sectors like financial, public health, and telecommunications.

Other simple systems are intended to be self-contained and generally apply to a specific scenario. For instance, Decision Support System for Water Infrastructure Security (DSS-WISE, no connection to WISE above) models dam and levee breaks to estimate economic and loss of life consequences (Altinakar et al., 2006). Those estimates are coupled with a particular metric that compares alternative flood mitigation strategies. While the mathematical metric combining different performance measures makes this model capable of being viewed as an optimization model, there is no systematic search through decision space to determine the best option. Instead, every possible alternative design is simulated and compared. To simulate a small number of alternatives may be feasible, but with multiple failures to simulate and a goal of considering the many solutions in the decision space, it quickly becomes computationally intractable.

2.2.3 Observations

The 24 different modeling efforts surveyed are classified according to model abilities and structure, as shown in Tables 2.1 and 2.2.

From the results of the survey in these tables, some conclusions about the state of infrastructure system modeling can be drawn. Much of present research on interdependent infrastructure concentrates on operation, simulation, and deterministic models. With a few exceptions, most models do not possess the capability of recommending mitigation decisions and quantifying the effect of these decisions with a systematic search through the decision space. Models are needed that measure system resilience in a variety of ways; they should be capable of recommending decisions, such as upgrades and retrofits, to improve resilience.

Table 2.1: Model Abilities in Detail

	Abilities						Structure		
Model Name	SIM	OPT	STR	OPS	DET	PRB	Net.	Agent	Other
FAIT (McLaren and Brown, 2005)	x			x	x		x		
MUNICIPAL (Lee et al., 2007)		x		x	x		x		
Markov Decision Model (Xu et al., 2006)		x	x			x	x		
Leontief IIO (Haimes and Jiang, 2001)	x		x		x				x
CIPMA (CIPMA, 2009)	x			x	x				x
I2SIM (Marti et al., 2008)		x		x	x				x
Petri-Nets (Gursesli and Desrochers, 2003)	x			x	x				x
UIS (Barrett et al., 2004)	x			x		x		x	
WISE (McPherson and Burian, 2005)	x			x		x		x	
MIN (Peeta et al., 2005)	x			x		x		x	
AIMS (Bagheri et al., 2007)	x			x		x		x	
Athena (Pederson et al., 2006)	x			x				x	
CISIA (Panzieri et al., 2004)	x			x		x		x	
COMM-ASPEN (Barton et al., 2004)	x			x		x		x	
CIP/DSS (Dauelsberg and Outkin, 2005)		x		x		x		x	
CI^3 (Pederson et al., 2006)	x			x		x		x	
CIMS (Dudenhoeffer et al., 2006)	x			x		x		x	
NSRAM (Baker et al., 2003)	x			x		x		x	
Nexus Fusion (Pederson et al., 2006)	x			x		x		x	
TRANSIM (Marfia et al., 2007)	x			x		x		x	
Network-Centric GIS (Abdalla et al., 2007)	x			x		x		x	
Repair Allocation (Karlaftis et al., 2007)		x		x	x			x	
DSS-WISE (Qi et al., 2006)		x		x	x			x	
NGTools (Pederson et al., 2006)	x			x				x	
Totals	18	6	2	22	8	14	3	17	4

Key to Table Abbreviations	
SIM	Simulation
OPT	Optimization
STR	Strategic
OPS	Operations
DET	Deterministic
PRB	Probabilistic
Definitions on page 6	

Table 2.2: Prior Work by Ability and Model Structure

Deterministic: 8			Probabilistic: 14		
	Optimization	Simulation		Optimization	Simulation
Strategy	0	1	Strategy	1	0
Operations	4	3	Operations	1	12

Two models omitted from ability breakdown due to incomplete information

Chapter 3

Models

The modeling framework presented in this thesis is intended to contribute to strategic and optimization models of interdependent infrastructure. The models aim to provide a framework to meaningfully quantify the effect engineering decisions have on improving the resilience of civil infrastructure systems. Recall that risk, R, is defined as

$$R = P \times C$$

or the probability of an event, P, times the consequences of that event, C. Resilience can be defined as the ability to return to a desirable system state "within an acceptable time period and at an acceptable cost" (Haimes, 2006). This definition of resilience is the goal pursued by the decision framework modeled here. Recovery time and costs are considered consequences and therefore part of system risk. Making engineering investment decisions that reduce the consequences, and therefore risks, after a natural disaster can be considered to improve system resilience. Thus, it is assumed that reducing system risk will result in increased resilience because of the reduction in expected recovery time and costs.

3.1 Base Model

The proposed framework is adaptable to a wide range of scenarios and combinations of infrastructure systems. Within this thesis, the framework addresses the risk of the system through attempting to lower the probability of consequences and thus to achieve greater system resilience. For development of the base model in this section, consider the situation illustrated in Figure 3.1. The scenario is abstracted from Princeville, North Carolina, which was badly flooded from back-to-back hurricanes in 1999. The development of the framework will demonstrate the general efficacy of the approach for reducing system risk in these types of scenarios.

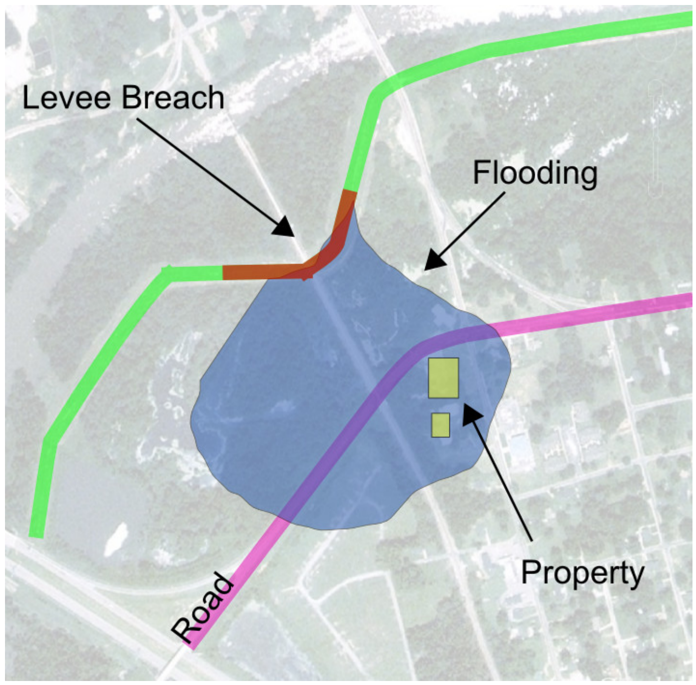

Figure 3.1: Basic Components of the System

In this scenario, a protective structure (here a levee), protects a system of infrastructures (a road and property). If the protection fails, the resulting consequences could cause multiple types of damage, including the disruption of lifelines and economic loss. Reducing risk requires decisions that reduce either the consequences to the affected infrastructures or the probabilities that the failure of infrastructures have consequences.

3.1.1 Decision Variables

The decision space must first be described. Define the following sets:

I = set of infrastructures, indexed by i

U^i = set of possible decisions for infrastructure i, indexed by u

For the particular infrastructures in the figure, $I = \{l, r, p\}$ where l indicates the levee, r the road, and p the property. Correspondingly, the decision variables are:

$$y_u^i = \begin{cases} 1 & \text{if infrastructure } i \text{ receives decision } u \\ 0 & \text{if infrastructure } i \text{ does not receive decision } u \end{cases}$$

This definition of decision variables ensures that a decision affects an entire infrastructure. The base model scenario considers aggregated infrastructure components as opposed to separate choices for individual components. The various decisions that could be made include upgrades and retrofits to existing infrastructure or even design decisions about future infrastructure. In this thesis, the term *upgrades* is frequently used to refer to the entire range of possible decisions.

Figures 3.2 and 3.3 represent possible upgrades to levee and road infrastructures. These upgrades are not the only possible decisions that the framework can handle. It is flexible enough to accommodate different upgrades to many types of infrastructures. For now these figures provide specific illustrations of the modeling possibilities.

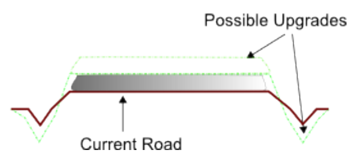

Figure 3.2: Possible Road Upgrades

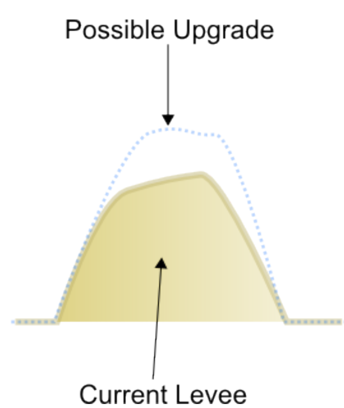

Figure 3.3: Possible Levee Upgrades

In later model instances, these decision variables will be redefined to allow lower-level decisions that consider a finer level of detail to be made for single components of infrastructure.

3.1.2 Metrics

As defined earlier, a function that quantifies a particular aspects of system performance will be defined as a *metric*. Each system metric should consider the collective contribution of many components to overall performance, including the contributions due to interdependencies of infrastructure components. For instance, while emergency responders may be prepared for post-disaster deployment, if the communications infrastructure is damaged, the metrics for emergency response should reflect the full impact of the lack of coordination.

Additionally, these metrics need to be capable of measuring the effect that engineering decisions would have on system performance. Measuring the effect of decisions makes it possible to implement a systematic search through the decision space for the solution that best fulfills the criteria. Finally, the time period of focus should be considered considered, whether a metric represents resilience before, during or after an event.

Serviceability

As seen in network models of infrastructure, critical infrastructures are often perceived as providing services to one another. To properly characterize the uncertainties in service, a metric to quantify the possibility that each infrastructure can provide a service is needed. In the context of road vulnerability, Berdica (2002) provides the following definition: "the serviceability of a link/route/road network describes the possibility to use that link/road/road network during a given time period." In this thesis, this definition is extended to include the possibility to use a particular infrastructure or infrastructure component, instead of confining the meaning to transportation concerns. This view of serviceability is similar to the view of connectivity in network infrastructure models. But as opposed to purely deterministic connectivity, the definition given allows the serviceability of infrastructures, like a water distribution system, to include a probabilistic analysis of failure. It is important to note that the desired level of serviceability might change before, during, and after a disaster. In the realizations of models that follow, serviceability is considered to represent the connectivity of the transportation network immediately after a disaster.

In Figure 3.1, the flooding due to a breach of the levee possibly renders the road unserviceable. Define a random variable F^l, which is equal to 1 when the levee has failed, and 0 otherwise. Given that $F^l = 1$, meaning that the levee fails, a simulation could provide an estimate for the level of water on the road (W^r) as a consequence of the levee failure. If the road can tolerate α^r feet of flooding before becoming unserviceable, then $W^r \leq \alpha^r$ corresponds to a serviceable road.

Let F^r be a random variable where $F^r = 1$ when the road is unserviceable. Based on the water level, this means that $\Pr(F^r = 1) = \Pr(W^r \geq \alpha^r)$. Assuming that a levee breach results in a pre-determined and given value for W^r, then $\Pr(W^r \geq \alpha^r) = \Pr(F^l = 1)$. Thus, if the breach causes the road to be unserviceable, the result is $\Pr(F^r = 1) = \Pr(F^l = 1)$.

Define the following function:

$$F^r(y_u^l, y_u^r) = \text{indicator random variable, based on the decision variables } y \tag{3.1}$$

Note that this function is dependent on the decisions made for the levee, y_u^l, and the road, y_u^r. Since 0 and 1 are the only possible values for road status, the expected unserviceability of the road can be determined as follows:

$$E[F^r(y_u^l, y_u^r)] = \Pr(F^r(y_u^l, y_u^r) = 1) \tag{3.2}$$

Property Damage

Another concern is calculating property damage and determining mitigation decisions. Measuring property damage could assist in deciding whether investment in mitigation before or rebuilding after a disaster is cheaper. Additionally, reducing the cost, or even the expected cost, of recovery directly increases the resilience of infrastructure.

The property indicated in Figure 3.1 is the focus of this metric in the base model. If considering damage from flooded infrastructure, as in this base scenario, damage could come from considering depth-damage curves as in Figure 3.4, or refer to Dutta et al. (2003). Let D_l^i be a random variable indicating the damage suffered by infrastructure i due to a failure of the levee. Using a depth-damage curve to calculate D_l^i gives rise to defining the random variable D^i, the damage suffered by infrastructure i. The probability distribution for D^i can be summarized by:

$$\Pr(D^i = D_l^i) = \Pr(F^l = 1) \tag{3.3}$$

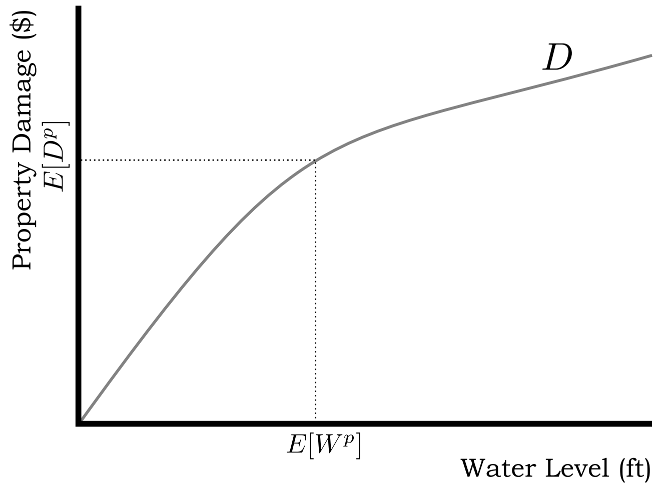

Figure 3.4: Depth-Damage Curve

The data from inundation models necessary for computing D^p, damage to property, is W^p, the water level on the property. This means that determining $E[D^p]$ is based on determining $E[W^p]$, as indicated by the dotted lines in Figure 3.4. This is mathematically defined as

$$
\begin{aligned}
E[D^p] &= \sum_{\substack{possible \\ damage}} \Pr(D^p = D_l^p) D_l^p \\
&= \Pr(D^p = D_l^p) D_l^p \\
E[D^p] &= \Pr(F^l = 1) D_l^p
\end{aligned} \tag{3.4}
$$

Because the expected water level can be modified through manipulating the probability of levee failure, $E[D^p]$ can also be affected by the probabilities of levee failure. As a result, it is possible to consider D^p as a function of decisions for the property and levee, though more accurately it might be considered as a function of water level and decisions made for the property. The function for expected damage to the property while considering the effect of decisions is written as follows:

$$E[D^p(y_u^l, y_u^p)] \tag{3.5}$$

Quite clearly, the function for damage to an infrastructure can extend beyond just property. Similar functions could be defined for other infrastructures. For instance, in the case of road damage, a joint probability function for damage based on water level and velocity could be used, and extending even further, the serviceability of the road could become a function of the damage.

Evacuation Time

If the road pictured in Figure 3.1 is part of an evacuation route for a population during or after a disaster, then it might be useful to measure the travel time on the road. Note that evacuation time will be developed with the goal of an emergency evacuation, though the framework could support pre-disaster evacuation planning. Instead of considering the road unserviceable if $W^r \geq \alpha^r$, consider the travel time across the road as a function of W^r. Let T^r be a random variable for the travel time on the road, and let T^r be a function of the water level on the road. Similar to the previous metrics, let the random variable for property damage as affected by decisions be $T^r(y_u^l, y_u^r)$, in an effort to consider $E[T^r(y_u^l, y_u^r)]$. It is not uncommon for road vulnerability studies to consider uncertain travel times (Lam et al., 2008).

Cost

Finally, another necessary metric is the monetary cost of engineering investment decisions, like upgrade costs. Define a cost function $c(y_u^i)$ for a subset of I that measures the engineering cost necessary to implement the decisions. This cost function is an extremely important metric to consider. Given a budget, B, another option is to use the metric to constrain upgrade cost, or $c(y_u^i) \leq B$.

It may also be necessary for certain scenarios to consider cost with the other metrics. This can be done in a variety of ways, a possible scenario for this occurs in Section 3.2.3.

3.1.3 Model Instances

The following mathematical optimization models are designed to obtain the decisions that best achieve the criteria according to the metrics defined in the previous section. Each instance measures how high-level decisions for aggregated components of infrastructure can reduce risk or increase resilience of the civil infrastructure system. Though simple, these models provide a foundation for later extensions that consider greater details and specificity.

All of these frameworks contain cost as either the metric or a limiting criterion with budget, since this is such a common issue for engineering decisions and especially infrastructure improvements.

Serviceability

By performing upgrades, the probability that a road segment is unserviceable can be reduced, thereby increasing serviceability of the road. That is, minimizing $\Pr(F^r(y_u^l, y_u^r) = 1)$, the expected unserviceability of the road, maximizes the serviceability. Let the budget limit be B. The following mathematical programming problem seeks minimization of unserviceability while complying with the specified budget.

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} \\
&\textit{minimize} \quad && \Pr(F^r(y_u^l, y_u^r) = 1) && && (3.6) \\
&\textit{subject to} \quad && c(y_u^l, y_u^r) \leq B && && (3.7) \\
& && y_u^i \in \{0, 1\} && \forall u \in U^i, i \in \{l, r\} && (3.8)
\end{aligned}$$

Property Damage

The goal is to minimize the expected property damage, $E[D^p]$. For this model instance, budget is the only constraint limiting what decisions can be made for the levee and property.

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} \\
&\textit{minimize} \quad && E[D^p(y_u^l, y_u^p)] && && (3.9) \\
&\textit{subject to} \quad && c(y_u^l, y_u^p) \leq B && && (3.10) \\
& && y_u^i \in \{0, 1\} && \forall u \in U^i, i \in \{l, p\} && (3.11)
\end{aligned}$$

Evacuation Time

Here, the goal is to reduce expected travel times on an evacuation route.

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} \\
&\textit{minimize} \quad && E[T^r(y_u^l, y_u^r)] && && (3.12) \\
&\textit{subject to} \quad && c(y_u^l, y_u^r) \leq B && && (3.13) \\
& && y_u^i \in \{0, 1\} && \forall u \in U^i, i \in \{l, r\} && (3.14)
\end{aligned}$$

Cost

This instance is similar to the serviceability model, but instead of using cost as a constraint, the model minimizes cost while keeping the unserviceability of the road below a certain threshold. Define β as the maximum allowed probability of unserviceability for the road, and then consider the following:

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} \\
&\textit{minimize} && c(y_u^l, y_u^r) && && (3.15) \\
&\textit{subject to} && \Pr(F^r(y_u^l, y_u^r) = 1) \leq \beta && && (3.16) \\
& && y_u^i \in \{0,1\} && \forall u \in U^i, i \in \{l,r\} && (3.17)
\end{aligned}$$

Note that if available decisions cannot reduce the probability of unserviceability beneath β, the problem will be infeasible.

In all of these instances, sensitivity analysis, better data inputs, and different combinations of metrics and constraints could be used to produce a fuller understanding of the situation. For example, the previous model instance could use sensitivity analysis to determine the costs associated with guaranteeing different levels of unserviceability in the road infrastructure.

Using these instances, it it possible to consider infrastructure risk at a high level and make decisions for aggregated components that reduce the risk. Such a view could be used for explicit designs, or it could be used for setting the design goals for each system before decomposing into individual subsystems and determining component decisions to reach those design goals. In the next section, infrastructures are considered to have subcomponents as opposed to the aggregated infrastructures of this section.

3.2 Independent Components

The base modeling framework can be extended to more complicated scenarios. In one possible extension, there could be spatial differences between different areas of an infrastructure. For example, a levee or roadway might have a significantly higher elevation in one location than in another. In this case, it might be advantageous to consider a spatial segmentation of the levee or road infrastructure, and separately consider the upgrades each segment could receive. This scenario appears in Figure 3.5. Discretization separates the components of

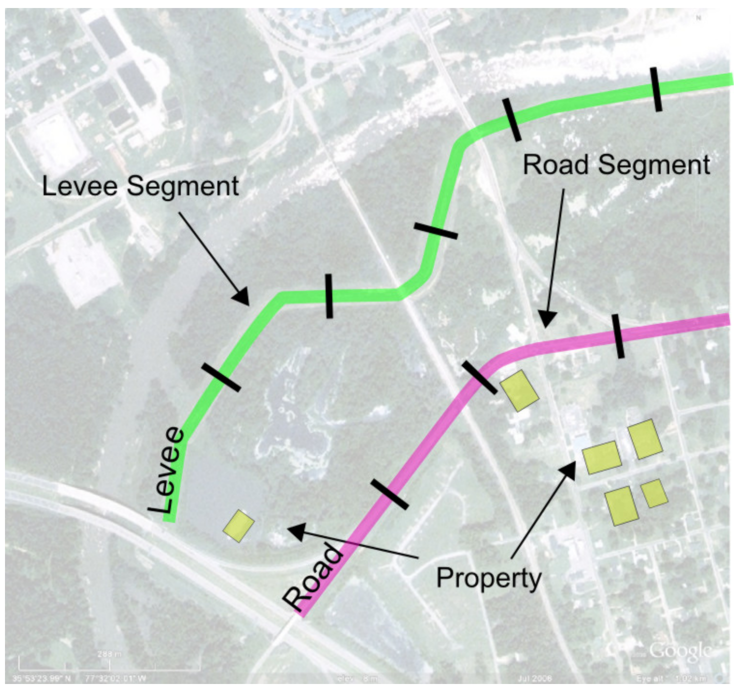

Figure 3.5: Discretized Levee, Road and Property

infrastructure that were aggregated in the previous model and allows consideration of the effects of decisions for individual components. In the remainder of this thesis the terms component and segment will be used interchangeably. Define the set J^i as the components of infrastructure i, indexed by j. Additionally, define $U^{i,j}$ as the set of possible decisions for component j of infrastructure i. The decision variables defined in the previous section need modification to capture new decision possibilities. Define

$$y_u^{i,j} = \begin{cases} 1 & \text{if component } j \text{ of infrastructure } i \text{ receives decision } u \\ 0 & \text{if component } j \text{ of infrastructure } i \text{ does not receive decision } u \end{cases}.$$

For these models $\mathbf{y}^i$ refers to the $|J^i| \times |U^{i,j}|$ matrix of decisions made for infrastructure i. The entry in the j^{th} row and u^{th} column of $\mathbf{y}^i$ is $y_u^{i,j}$.

This segmentation of infrastructures may result in a solution from a model instance that cannot be implemented, as the specifics of the scenario and component relationships may dictate that it is impossible to make a decision for a particular infrastructure component without also applying that decision to other components. An example of this issue is a road link discretized into two segments that would be required to receive the same decision on both segments. In this case, the decisions could be defined to apply to both segments, or a constraint could be added to force the necessary segments to receive the engineering decision.

The exact procedure for discretizing road and levee infrastructures is outside the scope of this thesis; different scenarios will require different methods. However, the expansion of the metrics from Section 3.1.2 is an absolute necessity for the modeling framework. In the next section, the metrics from the base model are extended to reflect the effect of spatially discretizing infrastructures.

3.2.1 Water Level Distribution

In this scenario it is assumed that a levee segment has two states, either functioning or failed. Spatial differences mean that the failure of sufficiently disparate levee segments causes different inundation for the other infrastructures. These assumptions make it necessary to associate the probability of a levee breach with a level of water that results from the breach for all infrastructure components. Additionally, it is necessary to estimate the probability distribution of the water level due to levee segment failure. Having an approximation of this distribution allows obtaining the probability distribution of water levels that affect each of the metrics.

To estimate the distribution of water level requires first selecting the combinations of levee failures that are of interest for levee breach simulation. The selection of failure combinations is a difficult issue and mostly outside the scope of this thesis. One way

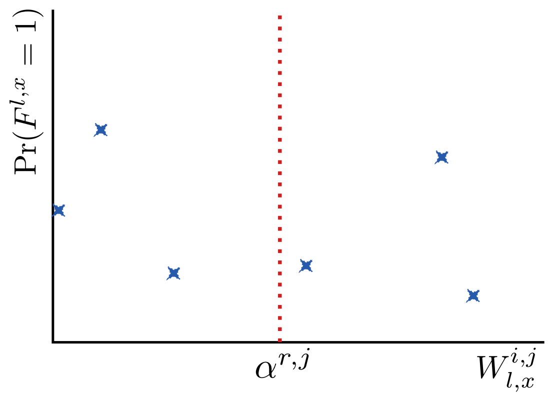

Figure 3.6: Probability that a Segment is Unserviceable based on Water Level

to determine which combinations are of interest might be to analyze the probabilities of each failure combination before upgrades, and select the combinations with the highest probability of failure. Another might be to evaluate inundation from every possible failure combination; however, for computational purposes, infrastructure like a levee may be too large to consider all $2^{|J^l|}$ combinations.

Leaving this concern aside, consider the scenario where only the failure of individual levee segment $x \in J^l$ is of concern. Mathematically, this is represented by a random variable $F^{l,j}$ which is 1 when levee segment j fails, and 0 when it does not. The hydrologic model is run for a breach for segment x and outputs the water level $W^{i,j}_{l,x}$, where $i \in \{r, p\}$ in this scenario, for all components of other infrastructures due to levee failure x. $W^{i,j}_{l,x}$ makes it possible to derive a probability distribution for the amount of water on each infrastructure component given a particular levee failure. An example of possible results for a particular road segment is in Figure 3.6. For a given segment j, each data point is generated by associating the water level $W^{i,j}_{l,x}$, from a levee failure with the probability $\Pr(F^{l,x} = 1)$, that the particular levee failure occurs.

Road Segment Failure

The probability distribution of the water level from the previous section is used to derive a distribution for the serviceability of a road segment. In Figure 3.6, the dotted line corresponds to $\alpha^{r,j}$, the maximum tolerable level of water on road segment j. Let $F^{r,j}$ be an indicator random variable equal to 1 if road segment j is unserviceable. In short, the sum of the vertical distances from the x-axis to each data point to the right of $\alpha^{r,j}$ provides an estimate of $\Pr(F^{r,j} = 1)$. A mathematical derivation for estimating the probability of unserviceability for the road based on the distribution of the water level follows.

Two methods for estimating the distribution of serviceability are possible, each requiring different assumptions about the levee failure. Let F^l be an indicator random variable that is equal to 1 if at least one segment of the levee has failed. Then one method for estimating the probability of road unserviceability requires first assuming that a levee failure has definitely occurred, that is, assume $F^l = 1$.

For road segments, the probability of not being able to traverse a road segment, j, is $\Pr(W^{r,j} \geq \alpha^{r,j}) = \Pr(F^{r,j} = 1)$. Let $LR^j = \left\{x : x \in J^l \text{ and } W^{r,j}_{l,x} \geq \alpha^{r,j}\right\}$, the set of all levee failures that result in an unserviceable road segment j. From the data given by inundation runs of levee breaches, it is possible to estimate the probability of unserviceability in the manner suggested in Figure 3.6:

$$\begin{aligned}
\Pr(F^{r,j} = 1) &= \Pr(W^{r,j} \geq \alpha^{r,j}) \\
\Pr(F^{r,j} = 1) &= \sum_{x \in J^l} \Pr(W^{r,j}_{l,x} \geq \alpha^{r,j} | F^{l,x} = 1) \Pr(F^{l,x} = 1) \\
\Pr(F^{r,j} = 1) &= \sum_{x \in LR^j} \Pr(F^{l,x} = 1) \qquad (3.18)
\end{aligned}$$

Remember that this probability is only an estimate and assumes that a levee segment definitely breaches somewhere. Considering more combinations of levee failures gives a more accurate estimate for the probability that a road segment is serviceable. For now removing the assumption that a segment has definitely failed and including $\Pr(F^l = 0)$, the probability that there are no levee failures at all, can be evaluated as follows:

$$\begin{aligned}
\Pr(F^{r,j} = 1) &= E[\Pr(F^{r,j} = 1 | F^{l,j})] \\
\Pr(F^{r,j} = 1) &= \overbrace{\Pr(F^{r,j} = 1 | F^l = 1)}^{Eqn.(3.18)} \Pr(F^l = 1) \\
&\quad + \Pr(F^{r,j} = 1 | F^l = 0) \Pr(F^l = 0) \qquad (3.19)
\end{aligned}$$

Equation (3.19) estimates the total probability that a road segment is unserviceable, $\Pr(F^{r,j} = 1)$, with a levee failure not necessary assumed. However calculated, this distribution opens the possibility of considering the serviceability of the road.

Other Metrics

The metrics for travel time and property damage can also use the distribution of water level on road segments and property components to estimate a probability distribution for each. Assuming functions are defined for each metric, the derivation of the associated distributions is similar to the derivation of unserviceability. Given that y is in the outcome space of either travel time or property damage, it is possible to consider for a component j, $\Pr(D^{p,j} \leq y)$ or $\Pr(T^{r,j} \leq y)$. First, define:

$$D^{p,j}_{l,x} = \text{ damage to property } j \text{ given levee breach } x \tag{3.20}$$

$$T^{r,j}_{l,x} = \text{ travel time on road segment } j \text{ given levee breach } x \tag{3.21}$$

The functions for these damage and travel times are given by simulations of levee breaches and the water level that results from these breaches. Next, using that data, define the following sets:

$$LP^j(y) = \left\{x : x \in J^l \text{ and } D^{p,j}_{l,x} \leq y\right\} \tag{3.22}$$

$$LT^j(y) = \left\{x : x \in J^l \text{ and } T^{r,j}_{l,x} \leq y\right\} \tag{3.23}$$

These sets help to estimate the probabilities that damage and travel time are less than a particular value:

$$\Pr(D^{p,j} \leq y) = \sum_{x \in LP^j(y)} \Pr(F^{l,x} = 1) \tag{3.24}$$

$$\Pr(T^{r,j} \leq y) = \sum_{x \in LT^j(y)} \Pr(F^{l,x} = 1) \tag{3.25}$$

As with serviceability, it is possible to obtain these estimates assuming $F^l = 1$ or that a levee failure is not a given.

3.2.2 Metrics

The estimates of the probability distributions for serviceability, property damage and travel time will be used here to extend the metrics for the scenario of independent components being considered. The goal of this scenario is to consider the performance of infrastructure system on the basis of the collective performance of individual components of each civil infrastructure, and these extended metrics provide mathematical foundations for quantifying system performance.

Serviceability

Define the random variable $F^{r,j}(\mathbf{y}^l, y_u^{r,j})$, which is 1 if road segment j is unserviceable and 0 if j is serviceable. Note that $F^{r,j}(\mathbf{y}^l, y_u^{r,j})$ is a function of the decisions applied to the road segment and levee infrastructure. To consider the performance of the entire road system collectively, the metric for serviceability must aggregate the serviceability of individual road segments into a single number. A possibility for the function measuring the unserviceability of the road system after upgrades is given by:

$$\frac{1}{|J^r|}\sum_j E[F^{r,j}(\mathbf{y}^l, y_u^{r,j})] \tag{3.26}$$

The sum of all random variables for unserviceability is used because the failure of each road segment is assumed to be independent of the failure of other road segments, and the result of Equation (3.26) is the average expected unserviceability of the entire road infrastructure. Note also that each road segment's serviceability equally contributes to total serviceability of the road infrastructure, but this metric could be modified to weigh road segments deemed more important accordingly.

Because $F^{r,j}(\mathbf{y}^l, y_u^r)$ is an indicator random variable, it is given that

$$E[F^{r,j}(\mathbf{y}^l, y_u^{r,j})] = \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 1) \tag{3.27}$$

and the average unserviceability could alternately be written as

$$\frac{1}{|J^r|}\sum_j \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 1) \tag{3.28}$$

Property Damage

Define the random variable $D^{p,j}(\mathbf{y}^l, y_u^{p,j})$ as the damage to property component j, which is dependent on decisions applied to the levee and the property j. Similar to serviceability, the goal is to consider the expected damage to all property. This would be

$$E\left[\sum_j D^{p,j}(\mathbf{y}^l, y_u^{p,j})\right] = \sum_j E[D^{p,j}(\mathbf{y}^l, y_u^{p,j})] \tag{3.29}$$

if the assumption is made that the damage to each property component is independent of the damage to other property. The estimate for the probability distribution of damage from

Equation (3.24) assists in obtaining this expected value. As with the serviceability of road segments, there is no weighing of the damage to different properties to make damage to one property imply a greater penalty than damage to another.

Evacuation Time

Define $T^{r,j}(\mathbf{y}^l, y_u^{r,j})$ to be the random variable for travel time and a function of decisions for the entire levee and road segment j. While it is possible to calculate the travel time over an individual road segment as in the base model, it is not entirely clear how the collective travel time of road segments should be considered. For now, the somewhat arbitrary decision is made that the sum of travel time of each road segment will define the total road infrastructure travel time. This is written as:

$$E\left[\sum_j T^{r,j}(\mathbf{y}^l, y_u^{r,j})\right] = \sum_j E[T^{r,j}(\mathbf{y}^l, y_u^{r,j})] \tag{3.30}$$

To assist in obtaining this expected value for travel time, Equation (3.25) should be used.

Cost

The cost is similar to the cost in the base model. Utilizing a generic cost function, $c(\cdot)$, it is still possible to consider $c(\mathbf{y}^i) \leq B$ as a constraint and $c(\mathbf{y}^i)$ as a metric that could be an objective in a mathematical programming problem.

3.2.3 Model Instances

Here generic mathematical programming problems that are similar to the base model instances in Section 3.1.3 are presented. The difference is that the instances below can capture the effect on system performance of decisions for individual infrastructure components. A limiting assumption, however, is that collective performance is independent of relations between components of the same infrastructure. This assumption is relaxed in Section 3.3.

Serviceability

As opposed to considering the expected probability that a road is serviceable, the objective of the model is to reduce the average unserviceability of all road segments. Budget is used as a constraint.

$$
\begin{aligned}
&\textit{Find} \;\; y_u^{i,j} \;\; \textit{that} \\
&\textit{minimize} && \frac{1}{|J^r|}\sum_j \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 1) && (3.31)\\
&\textit{subject to} && c(\mathbf{y}^l, \mathbf{y}^r) \leq B && (3.32)\\
& && y_u^{i,j} \in \{0,1\} \qquad \forall u \in U^i, i \in \{l,r\}, j \in J^i && (3.33)
\end{aligned}
$$

Property Damage

Again, budget is a constraint. The objective is to minimize total property damage to all property.

$$
\begin{aligned}
&\textit{Find} \;\; y_u^{i,j} \;\; \textit{that} \\
&\textit{minimize} && \sum_j E[D^{p,j}(\mathbf{y}^l, y_u^{p,j})] && (3.34)\\
&\textit{subject to} && c(\mathbf{y}^l, \mathbf{y}^p) \leq B && (3.35)\\
& && y_u^{i,j} \in \{0,1\} \qquad \forall u \in U^i, i \in \{l,p\}, j \in J^i && (3.36)
\end{aligned}
$$

Travel Time

Travel time is not calculated from any particular origin to a particular destination, rather the total travel time over all segments, as the metric dictates. Budget is the only constraint in this model instance.

$$
\begin{aligned}
&\textit{Find} \;\; y_u^{i} \;\; \textit{that} \\
&\textit{minimize} && \sum_j E[T^{r,j}(\mathbf{y}^l, y_u^{r,j})] && (3.37)\\
&\textit{subject to} && c(\mathbf{y}^l, \mathbf{y}^r) \leq B && (3.38)\\
& && y_u^{i,j} \in \{0,1\} \qquad \forall u \in U^i, i \in \{l,r\}, j \in J^i && (3.39)
\end{aligned}
$$

Cost

Here, the goal is to minimize the cost of upgrades, while maintaining a minimum level of serviceability and keeping expected property damage to a certain level. If it is impossible to conform to the maximum threshold for property damage with current decisions, then assign a penalty to the metric, equaling the expected damage over the desired level. Let θ_p be the maximum threshold for expected property damage. Let s_p^+ be the slack between θ_p and the expected property damage, or zero if expected property damage is greater than θ_p. Let s_p^- be expected property damage greater than θ_p or the excess damage. Add the constraint:

$$\sum_j E[D^{p,j}(\mathbf{y}^l, y_u^{p,j})] + s_p^+ - s_p^- = \theta_p \tag{3.40}$$

and change the objective function as in the following mathematical programming formulation:

$$\begin{aligned}
&\textit{Find } \; y_u^i \; \textit{ that} && \\
&\textit{minimize} && c(\mathbf{y}^l, \mathbf{y}^r, \mathbf{y}^p, s_p^-) && (3.41)\\
&\textit{subject to} && \frac{1}{|J^r|}\sum_j E[F^{r,j}(\mathbf{y}^l, y_u^{r,j})] \leq \beta && (3.42)\\
& && \sum_j E[D^{p,j}(\mathbf{y}^l, y_u^{p,j})] + s_p^+ - s_p^- = \theta_p && (3.43)\\
& && y_u^{i,j} \in \{0,1\} \qquad \forall u \in U^i, i \in \{l,r\}, j \in J^i && (3.44)\\
& && s_p^+, s_p^- \geq 0 && (3.45)
\end{aligned}$$

In this formulation, the cost function now includes the cost of having excessive property damage. This additional term ensures that mitigation decisions are balanced against excessive damage that can result if mitigations are not undertaken or those undertaken are insufficient. Note that if property damage is included in the objective function and removed as a constraint, then the objective function provides the entire cost of the decisions, or C. Also, if the monetary benefit of serviceability could be determined as B, it would be possible to optimize the net benefit, or $B - C$.

3.3 Networks

The basic assumption of the previous section was that components within an infrastructure independently contribute to performance of that system, but it cannot always be assumed that the performance of collections of components is unaffected by relations between individual components. For instance, if a path contains multiple road segments, and a single segment is unserviceable due to flooding, then that path is unserviceable. This is true regardless of the states of the other segments. It is more desirable to have contiguous road segments serviceable which results in higher road network serviceability. To address this issue, the effect on system and subsystem performance from the relationships between components of an infrastructure should be considered. This section examines the relationships between segments of a road and how they achieve serviceability for the road infrastructure and assist a population in reaching destinations.

3.3.1 Origin-Destination Pairs

Let O be the set of origin-destination (O-D) pairs, indexed by $o \in O$. This is the set of all locations a population could conceivably start from and would want to travel to. Let Q^o be the set of all paths between O-D pair o and let q_k^o be the k^{th} path between o. In the execution of the model framework, these sets and paths would be derived from pre-processing, using a k^{th}-shortest paths algorithm to generate the necessary number of paths for each O-D pair.

3.3.2 Metrics

The metrics of the previous section, specifically serviceability and travel time, are extended here to account for the benefits of contiguous serviceable road segments. The extension proposed has no impact on property damage, thus the associated metric will not be considered in this section. Additionally, the cost metric will be identical to that given in Section 3.2.2, because the same decision variables are used in this section.

Serviceability

To consider the serviceability of the network, it is necessary to know which O-D pairs are serviceable, which is in turn dependent on which paths in the network are serviceable.

For path q_k^o, consider $F_k^{r,o}$, which is an indicator random variable that is equal to 1 if the k^{th} path for o is unserviceable, and 0 if it is serviceable. Though this model framework attempts to capture the notion of collective performance depending on relationships between components and individual component performance, it will still be assumed that individual performance of components is independent. This means that the probability a single road segment is serviceable, $P(F^{r,j} = 0)$, is independent of the serviceability of other road segments, and the probability distribution derived in Section 3.2.1. A path's serviceability will be dependent, however, on the serviceability of the segments making up the path. Mathematically, the probability a path is unserviceable is:

$$\Pr(F_k^{r,o} = 1) = 1 - \prod_{j \in q_k^o} \Pr(F^{r,j} = 0) \tag{3.46}$$

or the complement of the probability that the path is serviceable. Similarly, including the effect of upgrades and other decisions, the following is obtained:

$$\Pr(F_k^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = 1) = 1 - \prod_{j \in q_k^o} \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 0) \tag{3.47}$$

If the serviceability for a certain O-D pair o is desired then consider the average serviceability of the paths of that O-D pair as follows:

$$\frac{1}{|Q^o|} \sum_{k \in Q^o} \Pr(F_k^{r,o} = 0) = \frac{1}{|Q^o|} \sum_{k \in Q^o} \prod_{j \in q_k^o} \Pr(F^{r,j} = 0) \tag{3.48}$$

and

$$\frac{1}{|Q^o|} \sum_{k \in Q^o} \Pr(F_k^{r,o}(\mathbf{y}^l, y_u^{r,j}) = 0) = \frac{1}{|Q^o|} \sum_{k \in Q^o} \prod_{j \in q_k^o} \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 0) \tag{3.49}$$

Extending serviceability to an entire network of multiple O-D pairs consists of two distinct options. The first option examines the average serviceability of all O-D pairs, and requires the calculation whether a particular O-D pair is serviceable, as opposed to the result in Equations (3.48) and (3.49), which measure the average serviceability of the paths for a particular O-D pair. Let $F^{r,o}$ be a random variable that is equal to 1 if O-D pair o is not serviceable, and 0 otherwise. To determine the unserviceability of o, this requires $\Pr(F^{r,o} = 1)$. This is identical to calculating the probability that all paths for o

are unserviceable. Mathematically, this is:

$$\Pr(F^{r,o} = 1) = \prod_{k \in Q^o} \Pr(F_k^{r,o} = 1)$$

$$\Pr(F^{r,o} = 1) = \prod_{k \in Q^o} \left(1 - \prod_{j \in q_k^o} \Pr(F^{r,j} = 0) \right) \tag{3.50}$$

To get the unserviceability of the network, the next step is summing Equation (3.50) over all $o \in O$ and averaging the serviceability of all O-D pairs as follows:

$$\frac{1}{|O|} \sum_{o \in O} \Pr(F^{r,o} = 1) = \frac{1}{|O|} \sum_{o \in O} \left[\prod_{k \in Q^o} \left(1 - \prod_{j \in q_k^o} \Pr(F^{r,j} = 0) \right) \right] \tag{3.51}$$

or including the effects of decisions:

$$\frac{1}{|O|} \sum_{o \in O} \Pr(F^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = 1) = \frac{1}{|O|} \sum_{o \in O} \left[\prod_{k \in Q^o} \left(1 - \prod_{j \in q_k^o} \Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 0) \right) \right] \tag{3.52}$$

The second option is to define an unserviceable road network as one where a single O-D pair is unserviceable. To assist in the development of this choice, define the random variable $F^{r,n}$ as 0 when the road network is completely serviceable and 1 if a single O-D pair is unserviceable. In this case, it is clear that the probability the network is unserviceable is equal to the probability that at least one O-D pair is unserviceable, or, alternately, the complement of the probability all O-D pairs are serviceable. Mathematically:

$$\begin{aligned} \Pr(\text{network is unserviceable}) &= \Pr(\text{at least one O-D pair is unserviceable}) \\ \Pr(F^{r,n} = 1) &= \Pr(\text{at least one O-D pair is unserviceable}) \\ &= 1 - \Pr(\text{all O-D pairs are serviceable}) \\ &= 1 - \prod_{o \in O} \Pr(F^{r,o} = 0) \\ &= 1 - \prod_{o \in O} (1 - \Pr(F^{r,o} = 1)) \end{aligned} \tag{3.53}$$

and $\Pr(F^{r,o} = 1)$ is given in Equation (3.50). When including the effects of decisions, the unserviceability of the road network is:

$$\Pr(F^{r,n}(\mathbf{y}^l, \mathbf{y}^r) = 1) = 1 - \prod_{o \in O} \left(1 - \Pr(F^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = 1) \right) \tag{3.54}$$

Obviously, this second definition of the unserviceability of the road network is stricter than taking the average unserviceability of all O-D pairs. The more applicable metric is likely to vary with the scenario and system of interest.

Evacuation Time

Serviceability only depends on the possibility of travel between an O-D pair but does not require the calculation of what particular path will be chosen. When considering travel time, it is necessary, however, to know how a decision is made between paths of varying durations. For this particular scenario, it is assumed that an entity traveling between an O-D pair has access to information regarding travel times and chooses the path of shortest duration. In scenarios where the evacuation routes for a population are assigned, this is not an unreasonable assumption.

For a particular path, k, of O-D pair o, the travel time on that path is defined as a random variable, $T_k^{r,o}$. Travel time can also be a function of the decisions made for levee and road infrastructures and is then defined as $T_k^{r,o}(\mathbf{y}^l, \mathbf{y}^r)$. For path k of O-D pair o, the network travel time as a function of travel time of individual road segments is:

$$T_k^{r,o} = \sum_{j \in q_k^o} T^{r,j} \tag{3.55}$$

and with upgrades the travel time is:

$$T_k^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = \sum_{j \in q_k^o} T^{r,j}(\mathbf{y}^l, y_u^{r,j}) \tag{3.56}$$

For a particular O-D pair o, travel time is defined as $T^{r,o}$, and is equal to the path of shortest duration:

$$T^{r,o} = \min_{k \in Q^o} \left\{ T_k^{r,o} \right\} \tag{3.57}$$

and considering the effects of decisions

$$T^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = \min_{k \in Q^o} \left\{ T_k^{r,o}(\mathbf{y}^l, \mathbf{y}^r) \right\} \tag{3.58}$$

The metric enables the consideration of evacuation time of a population between a particular O-D pair. To analyze system travel time for evacuations, one option is to consider the total evacuation time for all O-D pairs, or the average evacuation time in the network. Mathematically, the average evacuation time that is dependent on infrastructure improvements is:

$$\frac{1}{|O|}\sum_{o\in O} T^{r,o}(\mathbf{y}^l, \mathbf{y}^r) \tag{3.59}$$

Yet another option for evaluating a system's evacuation time is to consider the maximum travel time, which is addressed later.

3.3.3 Model Instances

These instances of the model framework provide possible methods for evaluating and improving road network serviceability and travel time. Because variations of these metrics that capture different aspects of their respective dimensions of system performance have been suggested, the context and goal of any implementation of these models should be considered to determine the suitable metric or metrics for the scenario.

Serviceability

Here, the chosen metric is average serviceability of all O-D pairs from Equation (3.52). The mathematical programming model is the following:

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} \\
&\textit{minimize} && \frac{1}{|O|}\sum_{o\in O} \Pr(F^{r,o}(\mathbf{y}^l, \mathbf{y}^r) = 1) && (3.60)\\
&\textit{subject to} && c(\mathbf{y}^l, \mathbf{y}^r) \le B && (3.61)\\
& && y_u^{i,j} \in \{0,1\} \qquad \forall u \in U^i, i \in \{l, r\}, j \in J^i && (3.62)
\end{aligned}$$

Evacuation Time

The instance displayed here attempts to minimize the maximum evacuation time in an effort to force decisions that affect the worst evacuation routes. Define a maximum evacuation time, E^*, which will be the objective function in the following model:

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} && && \\
&\textit{minimize} && E^* && && (3.63)\\
&\textit{subject to} && c(\mathbf{y}^l, \mathbf{y}^r) \leq B && && (3.64)\\
& && E[T^{r,o}(\mathbf{y}^l, \mathbf{y}^r)] \leq E^* && \forall o \in O && (3.65)\\
& && y_u^{i,j} \in \{0,1\} && \forall u \in U^i, i \in \{l,r\}, j \in J^i && (3.66)\\
& && E^* \in \mathbb{R} && && (3.67)
\end{aligned}$$

Other models with variations of the evacuation time metric could attempt to increase the ability of the road network to support shorter evacuation times. One additional view of evacuation time could penalize the travel time over a specific threshold for each specific O-D pair, similar to the cost for excessive damage from the model in Section 3.2.3.

Cost

Define E^o as the maximum allowable travel time for O-D pair o. For road networks, the following model instance attempts to obtain the lowest cost decisions to make travel possible under maximum acceptable travel times.

$$\begin{aligned}
&\textit{Find } y_u^i \textit{ that} && && \\
&\textit{minimize} && c(\mathbf{y}^l, \mathbf{y}^r) && && (3.68)\\
&\textit{subject to} && E[T^{r,o}(\mathbf{y}^l, \mathbf{y}^r)] \leq E^o && \forall o \in O && (3.69)\\
& && y_u^{i,j} \in \{0,1\} && \forall u \in U^i, i \in \{l,r\}, j \in J^i && (3.70)
\end{aligned}$$

The models presented show that the framework has the flexibility to handle a range of scenarios. In the next chapter, the applicability of this framework to civil infrastructures beyond those already presented will be discussed.

Chapter 4

Extensions

The flexibility of the proposed decision modeling framework allows its application to a variety of different scenarios. In this section, possibilities for extensions are discussed alongside approaches that govern the methodology for adding varying situations. This is not intended to be a statement of future work, instead it is meant as a guide for exploring some of the possibilities of the framework.

4.1 Protective Infrastructures

Abstracting the levee models from Chapter 3, the generalized scenario consists of a protective infrastructure that fails with a certain probability, and the failure results in consequences to other infrastructures. Obviously, this scenario is applicable to more coastal infrastructures than levees. During a hurricane, there are many potential failures of protective infrastructures that could result in other infrastructure damage. A few possibilities and the requirements necessary for modeling them are described in the following sections.

4.1.1 Sand Dunes

Sand dunes are constantly evolving due to natural processes and human activities such as beach and dune replenishment actions, and some further reading on dune evolution can be found in Mitasova et al. (2005). As a result of this evolution, the protection given to the coastal infrastructure by a particular sand dune changes with the current state of the dune. In Figure 4.1, a dune protects a civil infrastructure system. The figure represents a

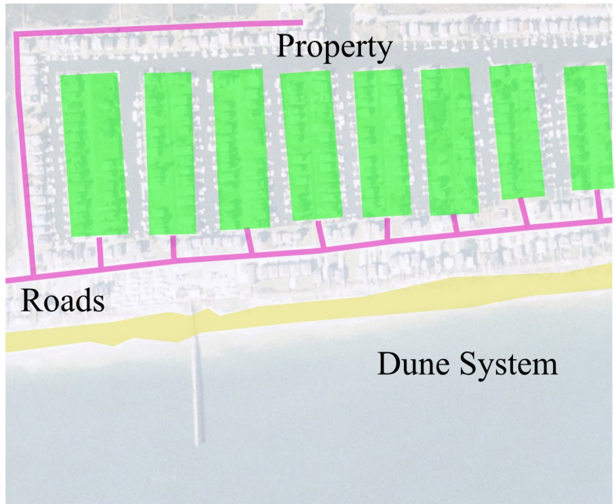

Figure 4.1: Sand Dune as a Protective Structure

specific point in time due to the dynamic nature of dunes. Despite the uncertainties in dune position, height, and sand conditions, it is nonetheless important to consider the protection they afford to beachfront communities, because dunes are a natural defense against storm damage.

The protection dunes give a beach community is similar to that a levee provides a community from upstream bodies of water. The difference is that dunes are dynamic elements of the natural environment. Yet management projects like beach nourishment and replenishment attempt to increase and maintain the protection dunes provide. With levees, it is necessary to calculate, based on various storm conditions, the probability that the levee fails. With dunes, it is not only necessary to calculate the probability that storm factors overwhelm and wash dunes away, but also to simulate their evolutions and their expected conditions at the time of the storm event. Addressing the evolution of dunes is not entirely dissimilar from incorporating degradation that levees and other structures experience over time. The types of decisions would still include choices such as upgrades and retrofits, but here it is necessary to consider how those decisions can potentially affect the evolution of the dune. A management policy might be a different maintenance schedule for the dune and the amounts of sand with each maintenance action.

Based on the expected condition of the dune, storm models could be run to determine water damage to infrastructure protected by the dunes. Thus, the decision variables for dune fields modeled as protective infrastructures will affect the expected condition of the sand dune and the expected damage from storm events.

More formally, let $s \in I$ be the dune field infrastructure. Let Z be a random variable indicating the condition of the sand dune, and define $Z(\mathbf{y}^s)$ to be the random variable for sand dune condition as affected by upgrades. As levee performance is calculated as the probability of failure, dune performance could be similarly represented, but with the added complication that performance must be dependent at least partly on dynamic conditions. As with levees, the various processes that affect dunes (see Roelvink et al. (2007) for some examples) could be aggregated into a single failure mode. Mathematically, the determination of $\Pr(F^s(Z(\mathbf{y}^s), \mathbf{y}^s) = 1)$, the probability that the sand dune fails, is required. This probability is a function of condition and decisions made for the sand dune.

Alternately, for this scenario and others, different types of failure could be considered by defining a random variable $F_k^{i,j}$, which is equal to 1 if component j of infrastructure i suffers failure type k. By taking into account the types of failure, evaluation of the failure modes of a protective infrastructure and the associated consequences with the different failure modes becomes possible. Of course, adding this complication is likely to increase computation time, especially if the dynamic characteristics of dunes are being addressed, and the trade-off between modeling accuracy and computation time should be carefully analyzed.

It should be clear that while incorporating sand dunes might require more intensive calculation and probabilistic modeling, the framework is capable, however, of including this type of extension. The only difference is the method of calculating the input, but when this is appropriately established, a mathematical programming model can be solved to obtain a set of decisions for satisfying the desired metrics.

Geotubes

It is possible to extend the modeling of dunes to include more detailed scenarios. Consider geotextile tubes, or geotubes. Generally they are intended to be used to protect property and shorelines from erosion and storm surges. Many times, they are used as beach dune cores (Heilman et al., 2008). In fact, geotubes can even be used to protect dunes and facilitate beach nourishment (Elko and Mann, 2007). Because of the similarities to dunes, there are instances where a geotube installation could be viewed as a type of an upgrade to a dune field. At other times, it might be necessary to consider them as a separate infrastructure. Of course, there are drawbacks to geotubes, and at times the failure of geotubes has been attributed to causing more damage than if they were not present (Heilman et al., 2008). The prime purpose of the proposed framework, however, is to quantify the effects of decisions, and determination of the impact of geotubes is a possible addition.

4.1.2 Serviceability

These models of protective infrastructure have something in common with the network models of critical infrastructure that consider supply and demand. While both view infrastructure as supplying a service for others, protective infrastructures can be viewed as supplying protection that is demanded by other infrastructures. Similar to considering the probabilities that a protective structure fails, the probabilities that a infrastructure can supply services demanded by another infrastructure could be calculated.

Consider the electrical power infrastructure. In a storm event, power outages can be modeled probabilistically (Liu et al., 2005). Define a random variable $F^{e,j}$ that is a 1 if component j of the electrical infrastructure, e, fails to operate. Next, $\Pr(F^{e,j} = 1)$ is calculated and could be used to derive the probability that another infrastructure, say water supply, w, fails to distribute water to a particular population. This probability could be mathematically noted as $\Pr(F^{w,j}(\mathbf{y}^e, \mathbf{y}^w) = 1)$, a function of the decisions made for the water and electrical systems. Based on this, the expected number of people that fail to get access to drinking water could be calculated. Other possibilities include the expected number of homes without power, or even the expected number of hospital beds without sufficient electrical and water resources.

The framework could also include bridge systems. While it is possible to model bridges as a part of the road network, bridges have unique failure modes and types of upgrades that could demand their inclusion as a separate subsystem of the transportation infrastructure. Then, the serviceability of an O-D path containing a bridge component becomes a function of the probability that the bridge is still serviceable. A random variable could be defined for the O-D pair, o, that uses the bridge and considers $\Pr(F^{r,o}(\mathbf{y}^r, \mathbf{y}^b) = 1)$, where b is a reference to the bridge system. This probability is the probability that o is unserviceable and would be a function of upgrades to the road and bridge infrastructure.

Essentially, the viewpoint for these extensions, protective and otherwise, is that there is an infrastructure that has probabilities of failing in different ways which gives rise to probabilities of consequences for dependent infrastructures. The proposed framework maintains that modifying the probabilities of consequences changes the risk to the dependent infrastructure, and potentially increases the resilience of the entire civil infrastructure system.

Chapter 5

Numeric Examples

5.1 Illustrative Example

The illustrative example considered is based on an abstraction of the Town of Princeville, North Carolina and is shown Figure 5.1. The figure also shows how the levee and road infrastructures are discretized, in this case arbitrarily, as no real data are used to consider the segmentation procedure. This example focuses on four levee segments and three road segments.

The steps used to solve this scenario are:

1. Gather data for current infrastructure conditions, such as elevations, budget for decisions, types of decisions and their benefits.

2. Spatially discretize the infrastructures of interest (levee and road here) according to an applicable segmentation procedure.

3. Obtain water levels for components of road infrastructure through storm and hydrologic inundation models using different combinations of infrastructure failures (here levee failures).

4. Calculate serviceability of each infrastructure component based on inundation levels.

5. Run mathematical programming model(s) to determine optimal decisions according to different metrics.

6. Test changed infrastructure system under other storm events, if desired.

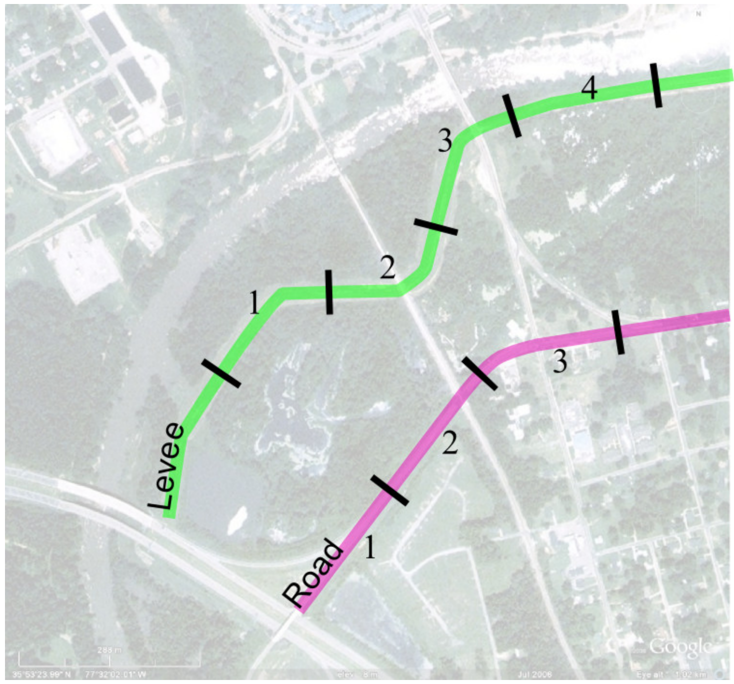

Figure 5.1: Illustrative Example

Steps (2) and (3) have already been completed for this example, however, hydrologic inundation and storm models were not used to obtain data for the flood characteristics in Figure 5.2. The floods represented in that figure are intended to be illustrative of the kind of data that would be needed from these types of models. As the model is not based on actual data, Step (1) will be completed as the need for each type of data arises during the development of the problem. Finally, to solve the problem, the model instance for Serviceability from Section 3.2.3 was linearized, allowing solutions to be obtained using Mixed Integer/Linear Programming solvers.

5.1.1 Calculating Serviceability

To calculate the serviceability of each road segment, the probability of failure of each levee segment must be calculated. This serviceability calculation is not necessary for the actual running of the model and is included to provide an initial measurement of the serviceability before any decisions have been made. The probabilities of failure for each levee segment for this example are given in Table 5.1.

It would be possible to consider combinations of levee failures. Given the small size of this problem, all possible combinations of levee segment failure could be calculated. As the flooding is not based on real-world numbers, it is instead simpler to only consider the failure of a single segment at a time. Given a failure of levee segment j, a hydrodynamic model calculates the flooding and subsequent water level on each road segment. In Figure 5.2, the inundation associated with individual levee breaches is shown. It is assumed for the purposes of this example that any road segment mostly covered by inundation in Figure 5.2 is an unserviceable segment due to flooding.

Based on these inundation results and the assumption of independent and mutually exclusive levee failures, the probability road segment j is serviceable, $\Pr(F^{r,j} = 1)$, is calculated for all road segments. Note that the sum of the probabilities of all levee failures is equal to 1. This means that Equation (3.18) on page 26 is necessary to calculate the unserviceability of a road. Recall that this requires the definition of the set:

$$LR^j = \left\{ x : x \in J^l \text{ and } W^{r,j}_{l,x} \geq \alpha^{r,j} \right\} \tag{5.1}$$

The sets calculated from the inundation appear in Table 5.2, where the left column indicates the road segments, and the right column contains levee failures that cause that road segment to be unserviceable.

For this example, based on Equation (3.18), $\Pr(F^{r,j} = 1)$ is just the sum of the probabilities of the levee failures in LR^j, or:

$$\Pr(F^{r,j} = 1) = \sum_{x \in LR^j} \Pr(F^{l,x} = 1) \tag{5.2}$$

The results of this calculation appear in Table 5.3.

Table 5.1: Probability of Levee Failures

Levee Segment j	$\Pr(F^{l,j} = 1)$
1	0.2
2	0.35
3	0.15
4	0.30

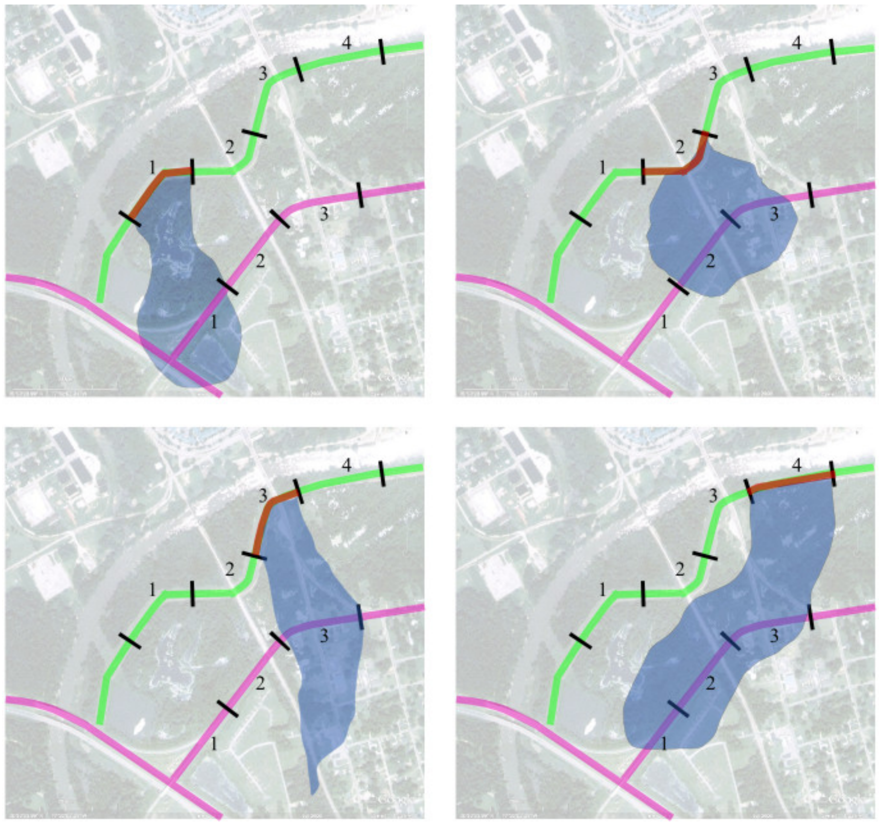

Figure 5.2: Inundation by Levee Breach

The totals demonstrate that:

$$\Pr(F^{r,1} = 1) = 0.5 \tag{5.3}$$

$$\Pr(F^{r,2} = 1) = 0.65 \tag{5.4}$$

$$\Pr(F^{r,3} = 1) = 0.8 \tag{5.5}$$

and thus the average unserviceability of the road network is:

$$\frac{1}{|J^r|}\sum_j \Pr(F^{r,j}(\mathbf{y}^l, \mathbf{y}^r) = 1) = 0.65 \tag{5.6}$$

5.1.2 Decision Types and Effects

For this model instance, only decisions that are upgrades to the four levee segments and three road segments are considered. For simplicity, it is assumed that an upgrade could be

Table 5.2: Levee Failures Causing Unserviceable Road Segments

Road Segment	Levee Failures
1	1,4
2	2,4
3	2,3,4

Table 5.3: Calculation of Initial Segment Unserviceability

		Road Segments		
		1	2	3
Levee Segments	1	.2	0	0
	2	0	.35	.35
	3	0	0	.15
	4	.3	.3	.3
Totals		.5	.65	.8

applied individually to a particular segment, without necessitating an upgrade to adjacent segments. The budget is chosen to be $B = 300$ budget units, and only two levels of upgrades are considered, upgrades of type 2 cost 50 budget units and upgrades of type 3 cost 100 budget units (upgrades of type 1 correspond to no upgrade will be performed on that segment). If $c_u^{i,j}$ is defined as the cost of decision u for component j of infrastructure i, then the cost of a particular decision is $c_u^{i,j} y_u^{i,j}$, and the cost constraint is:

$$\sum_{i,j,u} c_u^{i,j} y_u^{i,j} \leq B \tag{5.7}$$

To create a linear programming realization, the objective function must capture the effects that decisions have on the serviceability of the road segments. Let $b_u^{i,j}$ be the effect from decision u to component j of infrastructure i, and for this model instance the effect is the reduction of the probability of failure, or unserviceability, for infrastructure i. Thus, the effect of decision u on component j of infrastructure i is $b_u^{i,j} y_u^{i,j}$. To apply these benefits to the objective function, the following is a simple method for creating a linear realization of the calculation of unserviceability for a particular road segment j that considers the effect

Table 5.4: Upgrade Benefits

		Upgrade Type		
		1	2	3
Levee Segments	1	0	.05	.12
	2	0	.10	.18
	3	0	.07	.14
	4	0	.10	.18

		Upgrade Type		
		1	2	3
Road Segments	1	0	.10	.19
	2	0	.12	.23
	3	0	.15	.28

of decisions:

$$\begin{aligned}\Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 1) &= \sum_{k \in J^l} \Pr(F^{l,k}(y_u^{l,k}) = 1) - \sum_{u \in U^{r,j}} b_u^{r,j} y_u^{r,j} \\ &= \sum_{k \in J^l} \left(\Pr(F^{l,k} = 1) - \sum_{u \in U^{l,k}} b_u^{l,k} y_u^{l,k} \right) - \sum_{u \in U^{r,j}} b_u^{r,j} y_u^{r,j} \qquad (5.8)\end{aligned}$$

Note that this formulation explicitly defines $\Pr(F^{r,j}(\mathbf{y}^l, y_u^{r,j}) = 1)$ as a function of upgrades to the entire levee infrastructure and the particular road segment of interest. Using the previous equation, the average unserviceability of all road segments is:

$$\frac{1}{|J^r|} \sum_{j \in J^r} \left[\sum_{k \in J^l} \left(\Pr(F^{l,k} = 1) - \sum_{u \in U^{l,k}} b_u^{l,k} y_u^{l,k} \right) - \sum_{u \in U^{r,j}} b_u^{r,j} y_u^{r,j} \right] \qquad (5.9)$$

For this particular example, the benefit of decisions, in terms of the reduction of the probability of failure, appears in Table 5.4. Again, these upgrade types and benefits do not correspond to the results of any particular simulation model.

Another constraint is added to the problem to ensure that each segment of both infrastructures receives at most a single upgrade: otherwise it would be possible to have a negative unserviceability. The constraint is:

$$\sum_{u \in U^{i,j}} y_u^{i,j} = 1 \quad \forall i \in I,\ j \in J^i \qquad (5.10)$$

Finally, combining the constraints in Equations (5.7) and (5.10) with the objective

Table 5.5: Example Solution

		Upgrade
Levee Segments	1	1
	2	3
	3	3
	4	3

		Upgrade
Road Segments	1	1
	2	1
	3	1

function (5.9) the following Mixed Integer/Linear Programming problem is obtained:

Find $y_u^{i,j}$ *that*

$$\text{minimize} \quad \frac{1}{|J^r|}\sum_{j\in J^r}\left[\sum_{k\in J^l}\left(\Pr(F^{l,k}=1)-\sum_{u\in U^{l,k}} b_u^{l,k}y_u^{l,k}\right)-\sum_{u\in U^{r,j}} b_u^{r,j}y_u^{r,j}\right] \tag{5.11}$$

$$\text{subject to} \quad \sum_{i,j,u} c_u^{i,j}y_u^{i,j} \le B \tag{5.12}$$

$$\sum_{u\in U^{i,j}} y_u^{i,j} = 1 \quad \forall i \in I,\ j\in J^i \tag{5.13}$$

$$y_u^{i,j} \in \{0,1\} \quad \forall i\in\{l,r\}, j\in J^i, u\in U^{i,j} \tag{5.14}$$

5.1.3 Results

The model was implemented in AMPL and solved using CPLEX 11.2.0 on a machine with an Intel Core2 Duo CPU running at 2.4GHz with 2 GB of RAM. A solution was obtained in under a second, which was unsurprising considering the size of the problem. The optimal objective value is 0.15, meaning that the average unserviceability of the road is reduced by 0.50. The solution obtained is shown in Table 5.5.

The results of this illustrative example are encouraging, because the solution does not concentrate on the infrastructure of interest (the road network) in order to increase the serviceability. It is at least plausible that some of the interdependencies of the system have been captured appropriately by using this instance of the modeling framework.

Chapter 6

Observations and Future Work

The proposed framework is not without drawbacks. As developed for the various scenarios in this thesis, computational effort for simulations necessary to derive data could potentially be intractable. Also, many assumptions are made about the nature of components of infrastructure and their contributions to overall system performance. For instance, the serviceability of segments of a road are not truly independent, because a levee breach that floods one may be more likely to flood another based on the topography of the area.

Despite these drawbacks, the illustrative example demonstrates that the modeling framework provides an effective procedure for determining decisions that reduce collective risks to civil infrastructure. Equally important is that the metrics seem capable of capturing interdependencies in infrastructure and quantifying the collective performance of components. The models in this thesis can add another dimension to analysis and planning for more resilient infrastructure.

The proposed decision framework can be developed in multiple directions in the future. First, the inclusion of more realistic representations of infrastructures based on simulated and historical data could assist in creating models with increased applicability to the scenarios under consideration, leading to better insights and stronger conclusions. Also, post-disaster recovery is heavily dependent on the state of the system after a disaster, and the proposed framework provides a method for considering improvement to the infrastructure state at that time. Thus, another possibility is for the decision framework to be explicitly coupled with an operational optimization decision model for recovery after a natural disaster, with a goal of designing infrastructures that can ameliorate recovery processes.

As developed now, the metrics for the framework do not have explicit mechanisms for comparing the effects of decisions at different temporal scales. For instance, the ability of civil infrastructure to be more resilient in the short-term is not compared against long-term recovery effectiveness. Additionally, and perhaps the larger issue, the current decision framework considers only the effects on the infrastructure system due to damage from a single event. A useful development could be to produce a decision framework capable of measuring the effects of decisions at different temporal scales due to the influence of multiple events. A final issue is the incorporation of greater refinement of the uncertainties due to natural disasters. Combining these uncertainties with multiple temporal scales suggests the use of some form of multi-period stochastic programming to extend the framework to meet these additional requirements.

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