**NETWORK INTERDEPENDENCY MODELING FOR
RISK ASSESSMENT ON BUILT INFRASTRUCTURE SYSTEMS**

DISSERTATION

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Abstract

As modern infrastructures become more interconnected, the decision-making process becomes more difficult because of the increased complexity resulting from infrastructure interdependencies. Simulation and network modeling provide a way to understand system behavior as a result of interdependencies. One area within the asset management literature that is not well covered is infrastructure system decay and risks associated with that decay.

This research presents an enhanced version of Haimes' input-output inoperability model (IIM) in the analysis of built infrastructure systems. Previous applications of the IIM characterized infrastructure at the national level utilizing large economic databases. This study develops a three-phased approach that takes component level data stored within geographic information systems (GIS) to provide a metric for network interdependency across a municipal level infrastructure. A multi-layered approach is proposed which leverages the layered data structure of GIS. Furthermore, Monte Carlo simulation using stochastic decay estimates of each component shows how infrastructure risk, as a result of interdependency effects and component decay, changes over time. Such an analysis provides insight to infrastructure asset managers on the impacts of policy and strategy decision-making regarding the maintenance and management of their infrastructure systems.

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To my wife

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NETWORK INTERDEPENDENCY MODELING FOR RISK ASSESSMENT ON BUILT INFRASTRUCTURE SYSTEMS

I. Introduction

Built infrastructure systems and assets are so vital to modern society that their disruption can lead to severe consequences for a country's national security, economy, or public health and safety (U.S. Department of Homeland Security, 2009). Infrastructures are highly interconnected systems and study into these relationships is a new and rapidly growing area (Satumtira & Dueñas-Osorio, 2010). Understanding these relationships, and combined within an asset management framework, can facilitate better decision-making in the maintenance and management of infrastructure systems. As modern infrastructures become more interconnected, the decision-making process becomes more difficult because of the increased complexity resulting from infrastructure interdependencies. Authors have characterized the different types of infrastructure interdependencies (Haimes et al., 2007; Rinaldi, Peerenboom, & Kelly, 2001) and researched ways to model and simulate infrastructure behavior as a result of these interdependencies (Bagheri & Ghorbani, 2008; Brown, 2007; Pederson, Dudenhoeffer, Hartley, & Permann, 2006). Simulation and modeling provides a way to understand system behavior as a result of interdependencies.

This work presents an application of systems engineering principles to the study of infrastructure asset management and the issue of system decay. The dissertation surveys the literature in order to develop an understanding of the perspectives of asset managers. It finds that there is a shift in thinking taking place among asset managers from discipline-specific to more integrated systems-thinking in the management and maintenance of their systems. This shift offers the opportunity to explore systems engineering principles that might result in better decision-making by asset managers. The area specifically explored in this work is in simulation and modeling. Specifically, the input-output inoperability model (IIM) is explored and identified such that geographic information system (GIS) data can be leveraged in the understanding of system risk due to decay.

In the subsequent sections of this chapter, an overall summary of the dissertation research and its documentation are provided. First, the research motivation behind the modeling and analysis of built infrastructure systems as interdependent networks is presented. This section outlines the challenges and failures that asset managers experience in the performance of their duties and why re-thinking of infrastructure systems as interdependent networks is beneficial. Next, a high-level summary of the relevant literature which demonstrates a systems knowledge gap in the literature is presented. Following this, the problem statement, research objectives, and significant contributions for this work are articulated in their own respective sections. Finally, the chapter closes with a detailed overview of the remaining chapters and appendices of the dissertation document.

1.1 Research Motivation

Infrastructure asset managers face many challenges as they carry out their responsibilities in the operation, management, and maintenance of infrastructure systems.

A number of authors suggest that a change in perspective to a systems approach in the management of infrastructure is necessary in order to overcome these challenges (Godau, 1999; Hansman, Magee, De Neufville, Robins, & Roos, 2006; Lewis, 2006). Examples of these challenges include increased technical complexity of modern systems, greater external pressures from non-technical sources (e.g., the general public, local and national governments), the scale and vastness of infrastructure systems, inadequate tools in the analysis and management of infrastructure systems, and natural and human threats. Hudson, Haas, and Uddin (1997) argue that, although the practice of infrastructure asset management is not new, past practices have not always been systematic and that a change in management philosophy is necessary. These works highlight the need for addressing infrastructure management from a holistic, systems-centric approach.

As evidence of this viewpoint, this research has found that, indeed, much of the existing research in infrastructure management seems to address questions as they relate to a single infrastructure. Generally, infrastructure sectors (such as transportation, electrical, water/wastewater, facilities, etc.) are examined in isolation without regard to interactions with other sectors. Although there is a growing body of research into infrastructure interdependencies, which takes a network-view of multiple infrastructure systems, more work is needed in this area so as to better understand these "system of systems" relationships. Taking this kind of approach is necessary to answer complex questions regarding cascading effects and sources of infrastructure risk and vulnerability.

Understanding this, Hansman et al. (2006) lay out a research agenda to progress towards a comprehensive theory for the design and management of infrastructure systems. They highlight that infrastructure managers have failed in recognizing and managing the technical and social considerations of infrastructure systems and that this failure is one reason for the change of perspective. Changes to current research should include addressing these social considerations, strengthening the ties of research with industry practice, and taking an approach that seeks commonality across the infrastructure domains. Given these views, they detail a four-part agenda that is a fundamental re-thinking of infrastructure design and management. These elements are: (1) a comparative analysis across infrastructure domains, (2) creation of integrated socio-technical infrastructure models, (3) methodology development, and (4) application testing and evaluation. Their work is significant as it reinforces the need for understanding the interdependency effects of built infrastructure systems. The work in this dissertation specifically addresses Hansman et al.'s agenda item of methodology development as the dissertation presents a model which integrates disparate infrastructure systems and enables simulations and analyses across infrastructure systems. It is clear that understanding infrastructure interdependency effects through a systems approach will be beneficial to asset managers as they address both the technical and non-technical challenges of infrastructure management.

1.2 Background

Systems engineering offers the philosophical framework for addressing the challenges of asset management. This is demonstrated in a number of ways in the literature. For example, Cook and Ferris (2007) argue that systems engineering, as a multi-methodology, is an appropriate way to solve traditionally non-systems engineering problems. The International Council on Systems Engineering (INCOSE) developed the Infrastructure Systems Working Group (ISEWG) and published a special physical infrastructure issue which highlighted systems engineering applications to specific infrastructure types (Bauknight, 2004; Doukas, 2004; Krueger, 2004; Williams, McManus, Patel, & Williams, 2004). However, the work wherein systems engineering principles are explicitly used to address asset management problems stops with this issue. Instead, the literature demonstrates that there is a growing chorus among asset managers that systems engineering processes and approaches should be applied to asset management practices and problems (Godau, 1999; Hudson et al., 1997; Powell, 2010). Most recently, Powell (2010) documented leaders from throughout the engineering and infrastructure industry calling for more systems approaches as the industry collectively addresses the challenges of the U.S.'s decaying physical infrastructures. Additionally, the literature demonstrates that conceptual overlaps between the practices of asset management systems engineering processes already exist which suggest that applying a systems approach to infrastructure management is feasible. Highlighted in Appendix A, a comparative analysis between the fields of asset management and systems engineering is conducted which demonstrates the conceptual overlaps. The conclusion from this analysis is that core processes in asset management are already well-defined and codified within systems engineering. Therefore, a systems approach would indeed benefit practitioners of asset management.

The intersection of asset management and systems engineering is the viewpoint that this dissertation begins with in addressing infrastructure decay and its contribution to infrastructure risk. Surprisingly, infrastructure risk from decay is not well studied. In addressing infrastructure risk, researchers have focused on risk within the context of terrorist attack or natural disaster. Works such as Bagheri and Ghorbani (2008);

Cummings, McGarvey, and Vinch (2006); McGill, Ayyub, and Kaminsky (2007); and Lewis (2006) demonstrate this particular view, which exclude infrastructure decay as a source of risk and are representative of the majority of the work in the infrastructure risk literature.

An effort that does begin to address infrastructure decay as a source of risk comes from the Department of Homeland Security (DHS). In 2009, the DHS Science and Technology directorate sponsored the Aging Infrastructure workshop where the challenges and solutions to the nation's decaying infrastructure were debated and discussed. The workshop acknowledged that decay is a significant contributor of risk to the nation's infrastructures (Doyle & Betti, 2010), but the study of decaying infrastructure has not taken hold in the literature. Unlike the works centered on the risks to infrastructure from terrorist attack and natural disasters, few scholarly works exist that address understanding the effects to infrastructure systems from decay. With the exception of the national transportation system, there exists a gap in knowledge about the quantification and quantifiable effects of these decay factors on other infrastructures.

Another unexpected area where research seems to be lacking is in the modeling of infrastructure behavior as a network of connected edges and nodes. The National Research Council (2005) reported that the study of networks as a science and applications of principles from this science are still in its early stages. As modern infrastructures have become more interlinked, knowledge of an infrastructure's network properties would lead to insights and predictions on its behavior. For example, understanding cascading effects is of interest to asset managers as mitigation and recovery plans can be developed which would reduce the impact of triggering events (Zimmerman & Restrepo, 2009).

Interlinked infrastructures, which form a network of networks, give rise to the idea of system interdependencies and also methods in analyzing these interdependencies. In their seminal work, Rinaldi, Peerenboom, and Kelly (2001) establish the framework for infrastructure interdependencies. Relationships between two infrastructures that are mutually necessary for each other's operation is defined as an interdependency. The existence of interdependencies increases system complexity and creates behaviors that are not intuitively predictable but can be analyzed through various simulation and modeling methods. Infrastructure interdependencies modeling and the risks resulting from these interdependencies is an actively researched and growing field (Satumtira & Dueñas-Osorio, 2010). Appendix B of this dissertation provides a survey on the modeling and simulation methods of infrastructure interdependencies and classifies them into four broad groups: input-output inoperability modeling, agent-based modeling, graph theory (network) modeling, and other emerging models.

1.3 Problem Statement

Of the six core processes of asset management, two processes will be specifically addressed in this dissertation. The first of these is the information systems and data management process which requires that systems be in place such that relevant information is collected, available in a timely manner, valid and complete, and that archived data is accessible (Blanchard & Fabrycky, 2011). The other process is the risk assessment and management process which includes steps such as identifying risks, analyzing each risk, and developing mitigation strategies (Haskins, 2010; Roberts, Hughson, Smith, McIlveen, & Murray, 2006). The information and data process are inputs into the risk assessment and management processes. One such information system commonly used in asset management is the geographic information system (GIS).

GISs are data systems which relate the geographic location of a system component to other attributes of that component. From GIS data alone, it is possible to define the network attributes of an infrastructure as well as model the interconnected ties to other infrastructures. However, a common problem within these systems is that the network ties are often lacking, that is, the network has no topological connections and therefore the resulting data model is simply a collection of lines which are drawn near to points in space. A second problem is the use of spatial data for risk analyses. Many location problems are solved within GIS such as determining the shortest possible route or best location for a facility, but risk analyses are a class of problems not normally solved with spatial data. Typically, GIS is relegated to the visual display of risk analysis results, if integrated into the risk analysis and management process at all.

The power of a GIS is in its relational database structure. As a relational database, it relates different attributes of system components to each other. Geographic location is just one attribute and any number of attributes can be identified and stored within a GIS. Given this, attributes that indicate the aging process of system components can be stored and, in concert with network topology, a method might be able to leverage this data for a risk analysis from system decay. This dissertation addresses the issue of infrastructure risk from decay through the modeling of infrastructure systems as interdependent networks.

1.4 Research Objectives

The intent of this research is to develop a model that provides insight into the effect of decay as a contributor to risk associated with networked infrastructure systems. Given the research problem statement, the work contained within this dissertation addresses these problems through answering the following questions:

- How can risk to infrastructure be quantitatively modeled?
- What aspects of networked systems (that is, what metrics) are applicable towards infrastructure risk analysis?
- How do interdependencies of networks affect this analysis?
- How can the concept of infrastructure decay be modeled and simulated so as to produce a valid infrastructure network risk model?

1.5 Method Overview

The method chosen for this research is to simulate the propagation of risk through interdependent physical infrastructure systems. Specifically, input-output inoperability modeling (IIM) is explored and then modified such that the risks from physical infrastructure interdependencies can be determined. Two sources of data were required for this research. In the early stages of model development, simulated data was used in order to test the mathematical constructs for the modifications to the IIM. These simulated data consisted of small networks with few nodes to facilitate verification of the model output. Later stages of model development utilized GIS data on actual utility systems acquired from practicing asset managers. This data contained information on thousands of system components organized according to infrastructure type. This GIS data provided the basis for the network topology necessary for infrastructure interdependency modeling.

Data analysis consisted of applying the developed model to the data available and interpreting the resulting output from each application. An iterative procedure that simulated the inoperability of each system component was created and the results recorded. Each of these results provided a level of network interdependency generated by a particular system component. A static analysis of the model, where each component is analyzed only once, as well as a dynamic analysis, where Monte Carlo simulation is employed, were carried out as the modifications to the IIM were developed. In each trial, novel metrics articulating network interdependency effects were produced and these results and their applicability are discussed.

There are three major phases to this research. The first phase focuses on the development of a manageable problem. A smaller problem demonstrates general principles before applying these principles to a larger, more complex problem. In this first phase, the IIM is adapted from and applied to a six-node network representing a small infrastructure system. Monte Carlo simulation is incorporated into the model in order to explore the effect of decaying components. The second phase extends the model developed in phase one to a multi-layer model which leverages the multi-layer data structure of a GIS. Finally, the third phase of the research employs the developed multi-layer model on utility system GIS data for a small municipality such as an Air Force base. The data acquired for this final phase is representative of the state of infrastructure system data kept by asset management organizations and therefore tests the applicability and validity of the developed model.

1.6 Research Contributions

The research conducted in this dissertation will aid infrastructure asset managers in developing and choosing the best policies and strategies as their systems continue to age. Specific research contributions include:

- The simplification of the input-output inoperability model allows for the modeling of interdependencies and its effects in a networked system. Reducing elements of the interdependency matrix to Boolean values transforms the matrix to a directional adjacency matrix and ignores the strength of each connection, but this allows for the generalizability of the model.
- The proposed method finds that systems are often tree network structures and conventional network analysis methods will not account for the criticality of source nodes. Results from the proposed method will identify these critical components.
- Modeling utility lines as nodes within a network, rather than as network edges, further informs the model by accounting for their role as interdependent components of the system.
- Applying Monte Carlo simulation to the proposed model provides a means for projecting future maintenance requirements on aging systems as the asset management community suffers from a lack of studies and data on the reliability of infrastructure components.
- A multi-layer model is proposed for multiple infrastructure systems which abolishes the need to create a single, large network of nodes and instead leverages the layered data model of a GIS to aggregate infrastructure data.

- The interdependent nature of infrastructure systems naturally introduces cycles and loops within the system and creates the problem of non-invertability of the model. This work presents a solution to this problem by modeling cycles and loops in an acyclic manner as branches in a tree network.

1.7 Dissertation Overview

This dissertation follows the scholarly article format and presents three journal articles which document the research according to the phased approach outlined in Section 1.5. Chapter 2 describes a small problem of analyzing a simple six-node infrastructure system. It provides a brief discussion on the practice of infrastructure asset management and the use of modeling within that particular field. The chapter also provides a synthesis of the literature on infrastructure interdependencies as various authors diverge on the classifications of interdependency types. After examining the issue of infrastructure decay, the input-output inoperability model is described and modifications to the model are proposed. These modifications include the creation of the component decay score metric and integration of Monte Carlo simulation. The proposed model is applied to a simplified network problem and the chapter closes with a discussion on the simulation outputs and significant findings from this first phase. Chapter 2 has been submitted to *Structure and Infrastructure Engineering: Maintenance, Management, Life-Cycle Design, and Performance*.

Chapter 3 extends the six-node infrastructure model to a multi-layered model using layered geospatial data. This is an intuitive approach for infrastructure asset managers who employ GIS as part of their maintenance management systems. As Chapter 3 is intended to be a stand-alone article, a brief discussion of the IIM and its limitations is presented. Following this, the intersection of network analysis and GIS is examined. This examination concludes that network methods within GIS systems are limited to a small class of problems – the shortest path problem. Given the prevalence of GIS as a component of asset management systems, this work offers an opportunity to advance the state of knowledge in the field of asset management. The multi-layer model is presented through an example problem and the significance of the proposed approach concludes the chapter. Chapter 3 has been submitted to the *International Journal of Strategic Asset Management*.

Chapter 4 implements the developed models from previous chapters to data collected on four utility systems of a small municipality. GIS data alone provides the topology necessary to construct the interdependency matrices for each utility system. As outlined in the previous chapters, the models produce results which identify the most important nodes within each individual system and implements the multi-layer analysis method; the results of a Monte Carlo analysis simulating decay are then presented. The chapter highlights the differences in results between typical network metrics used in characterizing network structure and the results from the proposed modifications of the IIM. The chapter concludes with significant findings stemming from the third and final phase of the research. Chapter 4 will be submitted to the *Journal of Management in Engineering*.

Chapter 5 provides a conclusion to the document by summarizing the research effort. It begins by addressing each question of the research objectives, then presents the significant findings and key contributions of the work; finally, recommendations for future work are listed. Two appendices follow this chapter which provide an extended literature review on the overlap between systems engineering and infrastructure asset management and research methods in the area of infrastructure protection and modeling.

II. Infrastructure Decay Modeling with the Input-Output Inoperability Model (IIM)[1]

2.1 Introduction

In 2009, the Department of Homeland Security (DHS) Science and Technology directorate sponsored the Aging Infrastructure Workshop where participants discussed and debated the roles, challenges, and solutions to the nation's aging infrastructure. The workshop acknowledged that decay is a significant contributor of risk to the nation's infrastructure. The workshop and the subsequent publication of its findings partially fulfilled the DHS's stated goal to disseminate information as quickly as possible on technology and methods for addressing the problem of the United States' decaying infrastructure (Doyle & Betti, 2010). Efforts to hold this issue at the center of national attention have fallen short, as evidenced by U.S. government spending. From 1950 to 1970, the U.S. spent 3% of gross domestic product (GDP) on infrastructure and in the 1980s, this figure dropped to 2% of GDP; for China and India, the most recent figures are 9% and 5% respectively (Reid, 2008). Figures such as this show that U.S. policy-makers dedicate fewer resources to the construction, operation, and maintenance of the nation's infrastructure relative to other countries. Practicing engineers also contribute to this problem by failing to connect such funding shortfalls to relatable public consequences. Instead, dramatic infrastructure failures such as bridge collapses and natural gas line failures garner national media attention for a short while and then dissipate as quickly as

[1] The contents of this chapter were independently submitted for publication by Valencia, Thal, Sitzabee, and Colombi to *Structure and Infrastructure Engineering: Maintenance, Management, Life-Cycle Design and Performance* on February 12, 2013.

they appeared. Finally, the academic literature in the area of infrastructure decay is found to be lacking. Policy-makers are more concerned with infrastructure protection within the context of infrastructure risk as a result of extreme events such as a deliberate attack (i.e., terrorism), accidents, or natural disasters. However, the larger national consequence in terms of money, time, and safety will result from decayed infrastructure. Unfortunately, comparatively little has been written in recent decades on the effect of aging infrastructure.

Systems engineering and infrastructure interdependency analysis are two growing fields of study that researchers and practitioners in infrastructure asset management can use when studying the problem of infrastructure decay. This chapter synthesizes concepts from these areas in such a way that is useful to both practitioners and researchers of infrastructure asset management. Specifically, we propose a model that provides a risk ranking method that leads to a maintenance strategy by accounting for the networked and interdependent nature of multiple infrastructure assets and systems. Although risk ranking models in asset management have been suggested by others (e.g., Krishnasamy, Khan, & Haddara, 2005; Sathananthan, Onoufriou, & Rafiq, 2010), cascading effects as a result of network interdependencies are not explicitly addressed in these methods. This paper thus characterizes disparate infrastructure systems as interconnected, interdependent infrastructures and produces a risk ranking model based on component decay. Such a model would be useful in prioritizing infrastructure assets for tasks such as inspections or maintenance and repair. The paper is organized as follows. First, conceptual overlaps between systems engineering and asset management are presented to show that systems engineering concepts have broad applicability to asset managers. Second, a review of the academic literature on infrastructure interdependencies is provided that highlights the research methods and concepts on the topic. Finally, these two areas are combined and a framework based on the input-output inoperability model is proposed, which provides a new and useful method in the study and understanding of risk from infrastructure decay.

2.2 Asset Management and Modeling

The asset management paradigm is complex and still in nascent stages of development for civil engineers (Spatari & Aktan, 2013). Indeed, there is no single, widely accepted definition for the practice of infrastructure asset management, but there are common themes found in the literature (Cambridge Systems Inc, 2002; Grigg, 2003; Hoskins, Brint, & Strbac, 1999; Roberts et al., 2006; U.S. DOT, 1999). This section presents some of the predominant themes as they relate to infrastructure decay modeling.

One such theme is the criticality of quality infrastructure system data to asset managers. Inventory and condition state data are essential for performance model development (Rasdorf, Hummer, Harris, & Sitzabee, 2009). Continuing advances in geographic information systems over the past decade now make the collecting and maintaining of geo-spatial data, for example, common place. Knowing the location of the asset and its subsystems enables the use of spatial modeling techniques. Additionally, inspection history and maintenance data inform other modeling techniques in use by asset managers.

Modeling transforms data into information by, for example, revealing relationships between system components or enabling predictions for system behavior or individual component behaviors. For the model presented in the paper, data are used to estimate component decay which provides the current and future condition states of the asset. Through network dependency/interdependency analysis, these predicted condition states are then used to estimate the changing risk to the networked system over the life of the individual components.

Another theme in asset management is the recognition that engineering managers' primary duty is to allocate resources for infrastructure operation and maintenance to align with the enterprise's larger strategic goals. Modeling facilitates meeting these requirements, as forecasts are typical outputs for system models. These predictions inform decision-makers of possible system behavior such as likely future outputs, possibilities of failures, and other system scenarios. With such information, asset managers should develop optimized plans for the repair and maintenance of system components. Through focused and purposeful planning, asset managers can better articulate or allocate repair and maintenance resources in order to support enterprise objectives. Indeed, the model suggested in this paper provides a predictive means for estimating the failure likelihood of a single component, its impact across its own network, and the ability to formulate alternative maintenance policies.

A final theme encountered in the asset management literature is the idea that differing system perspectives lead to different management approaches. Specifically, the International Infrastructure Management Manual (IIMM) (Roberts et al., 2006) suggests two different perspectives, "top-down" versus "bottom-up" asset management, which lead to two different approaches in plan development. A "top-down" approach is the practice of system decomposition whereby engineers first understand a system as a single entity and then decompose the system into smaller and smaller subsystems or components for greater understanding. Such an approach is considered a core function of asset management. Its converse is the “bottom-up” approach whereby system information is collected at the component level. Figure 1 highlights how advanced asset management organizations have moved beyond the top-down approach and practice bottom-up approaches to inform their decision-making. Some argue that true asset management, being enterprise-wide, entails managing data both vertically and horizontally within the system and thus requires that *both* a top-down and bottom-up approach be simultaneously implemented (Cambridge Systems Inc, 2002).

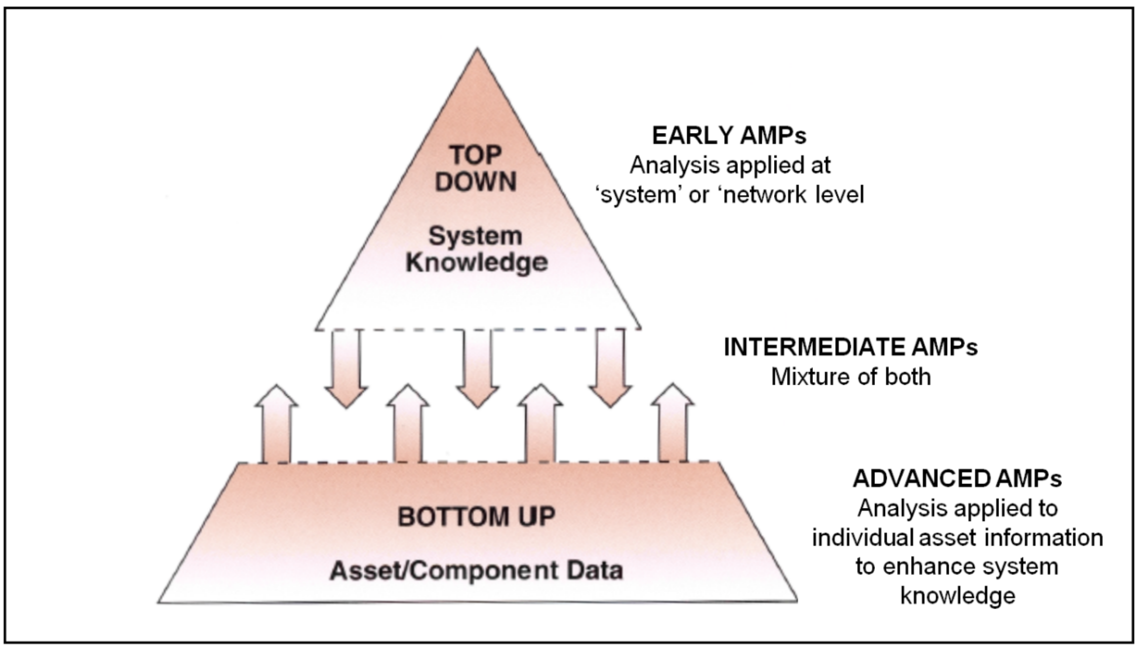

Figure 1. Top down vs. bottom up approach. (Roberts et al., 2006)

The understanding of the infrastructure system from both top-down and bottom-up perspectives is necessary for the decay model presented in this paper. Top-down views are needed since infrastructure systems are networks and methods utilizing network analysis, specifically interdependent network analysis, should be considered in the core stages of asset management practice. Decomposition of these networks into subsystems, and ultimately collection of data at the component level, leads to a bottom-up view of the system. Such a dual perspective is necessary as the model requires decay data for each component in the system.

2.3 Infrastructure Interdependencies

Infrastructure systems are highly interconnected systems within theselves (components are networked together to function as a single system) and to other systems (outputs from one system are inputs to another). These interconnections, whether internal or external, create system behaviors that can be predicted if modeled or simulated correctly. The results from predicting infrastructure behavior would ultimately result in maintenance policies or initiatives for the optimized management of infrastructure. Because individual infrastructure systems are not stand-alone and require other systems to function, the idea of infrastructure interdependency and identifying the risks as a result of these interdependencies is an actively researched and growing area of study (Cummings et al., 2006). The following is a brief review of the concept of infrastructure interdependencies.

2.3.1 Dependency versus Interdependency.

Although focused on critical infrastructure protection, the seminal work of Rinaldi, Peerenboom, and Kelly (2001) has facilitated research in the area through its basic definitions on interdependent infrastructures. To begin, Rinaldi et al. (2001) establish the difference between the terms *dependency* and *interdependency.* An infrastructure dependency is a uni-directional relationship between two infrastructures.

In other words, one infrastructure relies on the output of a different infrastructure (or infrastructures) and this relationship is not reciprocal. In contrast, an infrastructure interdependency is a bi-directional relationship between two or more infrastructures in which the infrastructure outputs are mutually relied upon by the infrastructures involved. In other words, an interdependency exists when systems are dependent on each other. Conceptually simple, the notion of interdependencies increases the complexity of a system and this complexity leads to behaviors by the "system of systems" that is not intuitively predictable.

2.3.2 Interdependency Types.

Rinaldi et al. (2001) furthered the idea of infrastructure interdependencies through categorizing interdependency types. They establish that four types exist: physical, cyber, geographic, and logical. Others have provided similar classifications of interdependencies (e.g., Haimes et al., 2007; Johansson & Hassel, 2010; McNally, Lee, Yavagal, & Xiang, 2007) and their works are compared in this section. Remaining with Rinaldi et al.'s (2001) framework, the four interdependency types are briefly defined here. *Physical interdependencies* are relationships based on material outputs from one infrastructure passed to another as a material input. *Cyber interdependencies* exist when information is the entity passed between infrastructures. *Geographical interdependencies* are based on physical proximity, e.g., infrastructures are located such that a localized event affects the status of these infrastructures. *Logical interdependencies* exist when there is a bi-directional relationship; this relationship is neither physical, cyber, nor geographical; and a logical reasoning is used to define the interdependent relationship.

A variation of Rinaldi et al.'s (2001) work, Haimes et al. (2007) incorporates *economic interdependencies* and suggest that these interdependencies result in the ability to predict the economic behavior of whole infrastructure sectors or an entire geographic region. A regional economic interdependency is similar to a geographic interdependency by spatially bounding the infrastructures of interest. An inter-sector economic interdependency captures the linkages of entire economic sectors without the bounds of geography. Haimes et al. utilize the well known economic input-output analysis method for their study of economic interdependencies.

Finally, McNally et al. (2007) and Johansson and Hassel (2010) offer a simpler framework for infrastructure interdependency by proposing only two classifications of interdependency types: *functional* and *spatial*. Their framework suggests that Rinaldi et al.'s (2001) classes of physical, cyber and logical interdependencies be classified under the broad term of functional interdependency while spatial interdependencies receive the same treatment as a geographical interdependency. Figure 2 shows these various classifications and highlights the overlap in concepts between the three classification frameworks.

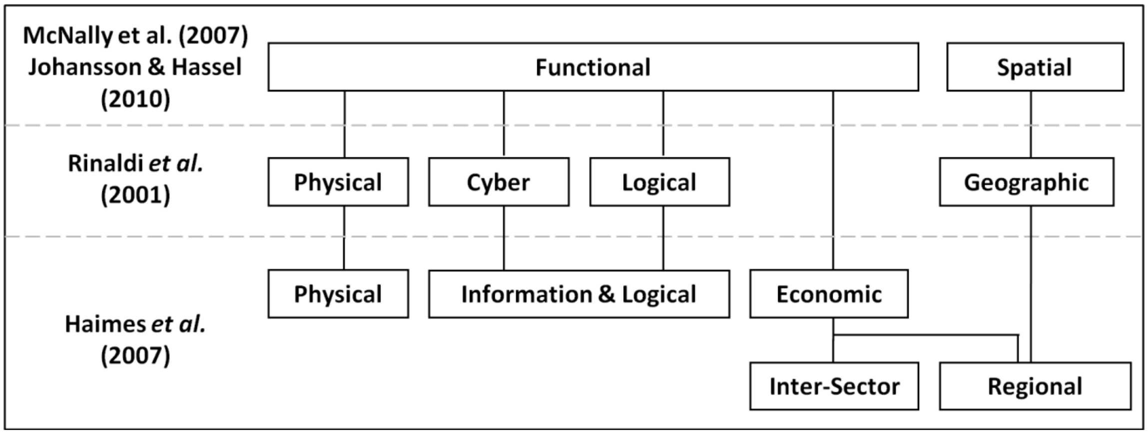

Figure 2. Graphical comparison of three interdependency classification frameworks.

Interdependency types are important to understand as they contribute to differences in relationships within and across infrastructures. For example, when dealing with time scales, input-output exchanges based on cyber interdependencies occur in very short cycles compared to physical exchanges. As another example, spatial and functional interdependencies differ from each other as spatial interdependencies are static (do not move) whereas functional interdependencies are dynamic (quantities involved in the input-output exchange vary). Understanding the differences between the interdependency types is necessary in building accurate and realistic models and simulations.

2.4 Infrastructure Decay

The infrastructure of the United States was designed and built largely after World War II, thus making the age of these systems 50 to 60 years old. In the American Society of Civil Engineer's (ASCE) 2009 infrastructure report card, several systems were highlighted as either having or are nearing their expected design life of 50 to 70 years (ASCE, 2009). Additionally, the lack of public interest and therefore public funding has led to a significant lack of maintenance, thereby contributing to infrastructure decay. Engineering leaders generally agree that the primary problem faced by all infrastructure sectors is the decaying of their systems (Powell, 2010). However, as noted earlier, engineers have not articulated well the linkage between infrastructure decay and consequences to the public.

Infrastructure decay is made up of four components: time, exposure, lack of maintenance, and usage (Zimmerman, Restrepo, & Simonoff, 2010). The significance of each of the four components on decay will vary across different infrastructure types. For example, underground utilities are subject to different environmental exposure than say bridges and roads. Exposure, therefore, might not be a consideration for understanding decay in underground utilities. As another example, age may not be indicative of a decaying infrastructure. The New York City transit system, one of the oldest in the nation, showed its resiliency in returning to operation after the subway damage and shutdowns following the September 11, 2001, attacks (Zimmerman et al., 2010) and, more recently, Hurricane Sandy flooding (Santora, 2012; Snider & Everett, 2012). In addition, the effect of decay is different on different infrastructure systems. For example, the Army Corps of Engineers recently found deteriorated storm water drainage pipes and degraded pumping systems along a 6-mile stretch in Brookport, Illinois (Flesher & Burdeau, 2013), and the ASCE has documented the deterioration of the nation's roadways (ASCE, 2011). Should the 6-mile segment of the flood protection system fail and an equally long or longer segment of roadway fail, the effects from such failures, obviously, are not equitable. Take any two different infrastructure systems and the effects from decay will be different given the disparate services each system offers. So determining the effect of decay is further complicated since its effect varies across infrastructure types.

This chapter offers a method to better understand the problem of infrastructure decay and its relation to risk. This currently open question has relevance to asset managers for the following reasons. First, a decayed system will be much less resilient in responding to extreme events. If the future does hold more extreme weather phenomena due to global warming, then the nation's infrastructure will be at more risk and relevant policy and management strategies cannot be developed without understanding the underlying cause and effect of risk from decay. Second, as the cost of system rehabilitation increases considerably as time (or decay) increases, so does risk. Although notional, Capers and Valeo (2010) note that decreases in levels of infrastructure service and increases in required maintenance will accelerate over time. Thus, decay results in a non-linear relationship to degraded service and increased cost. Finally, correlating decay and risk is no easy endeavor. Unlike actuaries in the insurance industry, infrastructure managers may not have historical data that can provide a decay-risk profile. The National Transportation Safety Board may be an exception as they implement biennial bridge inspections as part of their asset management strategy. Other infrastructure sectors would be served well doing the same, but in the mean time, methods and techniques will have to be developed, and research conducted, to fill this knowledge gap. This paper offers a contribution to the existing literature by proposing a model that articulates the risk of decaying infrastructure components on an interconnected, networked system.

2.5 The Input-Output Inoperability Model and Risk Assessment from Aging Infrastructure

Acknowledging the interdependent nature of infrastructure systems leads to considering ways to model and simulate infrastructure network behaviors. Methods utilizing various techniques exploring the effects of interdependent infrastructures include agent based modeling, graph theoretical methods, social network analysis, system dynamics, and input-output analysis (Satumtira & Dueñas-Osorio, 2010). This paper presents a method based on the input-output inoperability model (IIM) developed by Haimes and Jiang (2001) which is an adaptation of the Leontief input-output analysis. Many extensions and adaptations to the IIM have been proposed such as the Dynamic IIM (DIIM), the Multi-Regional IIM (MR-IIM), and others (e.g., Barker & Haimes, 2009; Haimes et al., 2007; Santos, 2008). The model presented herein proposes an adaptation to the IIM, but with several departures that allow for the modeling of infrastructure risk as a result of decay.

Based on Leontief's work on economic interdependencies, the IIM models the effects of a perturbation in a network through an understanding of node interdependencies throughout the network. Leontief's input-output (I-O) model makes use of economic databases that track exchanges between economic sectors and, thus, establishes a measure of interdependency between these sectors. The exchanges of resources and goods between sectors are viewed as an input or output of a sector, hence the title of the modeling method. An I-O analysis is able to determine the system-wide effects of a perturbation in one or more sectors. Similarly, the IIM is interested in understanding the effects of a perturbation and also takes advantage of data-rich economic databases; however, rather than understanding economic impacts, the IIM seeks to understand the propagation of "risk of inoperability."

The risk of inoperability, or simply inoperability, is the key adaptation to Leontief's I-O model. Haimes and Jiang (2001) and Haimes (2009) define inoperability as "the inability for a system to perform its intended function." Inoperability is likened to the concept of "unreliability" which describes the probability of failure for a system. Inoperability is expressed as a value between 0 and 1 where zero denotes no inoperability (flawless operation) and one denotes complete inoperability (complete failure). The authors suggest that these inoperability values be developed from expected values of risk based on the likelihoods of failure and levels of failure. Thus, the IIM proposes that inoperability equates to risk and that these risks are passed between infrastructure systems given the interdependent nature of nodes in a network. The compact matrix notation of the IIM is presented below:

$$\mathbf{q} = \mathbf{A} \cdot \mathbf{q} + \mathbf{c} \tag{2.1}$$

The operation to solve Equation 2.1 is simply:

$$\mathbf{q} = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c} \tag{2.2}$$

Vector **q**, the *damage vector*, is the final solution to the model and is a collection of inoperability values for all *n* infrastructures modeled in the system. Thus, this vector indicates the level of lost capacity of all infrastructures after the introduction of some perturbation in one or more infrastructures in the system. Vector **c**, the *scenario vector*, is the collection of introduced perturbations in the system. A scenario could be a natural disaster or terrorist attack, and this vector provides a means of entering the direct damage to infrastructures 1 to *n* as a result of the modeled scenario. **A**, the *interdependency* *matrix*, is an *n x n* matrix that captures the extent of interdependence among infrastructures. For example, if the complete failure of infrastructure *j* results in the complete failure of infrastructure *k*, then element $a_{kj} = 1$. As another example, if the complete failure of infrastructure *j* results in a 50% failure of infrastructure *k*, then element $a_{kj} = 0.5$. If there are no connections between infrastructures, then element $a_{kj} = 0$. Therefore, matrix **A** is a normalized, square matrix that represents the probability of transferring inoperabilities from one infrastructure to another. Finally, the **I**-matrix is simply an *n x n* identity matrix used for solving the IIM model. See Haimes and Jiang (2001) and Haimes (2009) for a full treatment of the derivation of the IIM.

With the IIM briefly explained, this paper presents four departures from the IIM and aids in the study and understanding of infrastructure decay for asset managers. First, the scale of this proposed model is limited to built infrastructures where the network model represents system components as nodes and the system interdependencies of these components (i.e., physical, cyber, logical, and geographical) are edges, or links, of the network. A “top-down” approach to modeling is required as a network view of the infrastructure system must be taken. Understanding the nodes and linkages between these nodes is needed to build the interdependency **A**-matrix.

Second, rather than attempting to specify the likelihood and degree of interdependency, this model proposes that any interdependency (whether physical, cyber, logical, or geographic) be specified as Boolean, either 0 or 1, in the interdependency **A**-matrix. Thus, if component *k* has no dependency to component *j*, then $a_{kj} = a_{jk} = 0$. Should an interdependency exist, say *j* is dependent on *k* functioning, then $a_{kj} = 1$ and $a_{jk} = 0$. Although it could be argued that this represents a significant limitation by ignoring the degree or “strength” of the relationship, limiting the elements of the **A**-matrix to Boolean values simplifies the IIM modeling. In fact, a major limitation to the IIM is the extensive data collection and data mining that might be necessary in determining the **A**-matrix as suggested by its authors. Use of Boolean values mitigates this limitation as the proposed model now only requires that the direction of an interdependent connection be known. The simplification of the **A**-matrix creates a more generalized model, thereby increasing the potential for use of the IIM framework.

The third departure from the IIM concerns the use of probability distributions for elements of the **c**-vector. Probabilistic IIM methods have already been proposed (Barker & Haimes, 2009; Haimes et al., 2007; Santos, 2008), but the current model differs as it proposes to (1) employ component decay curves and (2) apply such curves for each component in the system. This model seeks to illustrate the effect of decay across the networked system and transforms the **c**-vector from a scenario vector with static inoperability values, typically used to represent probabilities of extreme events, to a decay vector, denoted as **c***, which represents component decay curves for all components in the system. With this transformation, a challenge is introduced whereby probability distributions for decay must be collected for all components of the system.

This challenge is significant. Such decay curves do not readily exist for many infrastructure assets, yet implications, such as cost, based on these curves are freely discussed (Capers & Valeo, 2010). Some work exists in the literature that addresses the development of life expectancies for infrastructure system components, but as Datla and Pandey (2006) acknowledge, these efforts are problematic since industry does not have adequate data to develop these failure estimates. Others suggest the use of nonprobabilistic, qualitative methods such as risk-matrices and ordinal scaling to simplify the evaluation of components (e.g., Sathananthan et al., 2010), but such suggestions do not capture the stochastic, time-dependent nature of decay. These methods instead only offer a single "snapshot" of component risk at the time of evaluation. They offer no predictive capabilities for changes in risk over time. The incorporation of component decay curves would allow for such a dynamic analysis. If a "bottom-up" asset management approach is put into practice, asset management organizations might either already have such component-level decay data or are working towards the collection of it. Although challenging, collecting this data is a necessary component towards advanced asset management practice.

The final and fourth departure is the introduction of the component decay score, $decay\_score_i(t)$. Most IIM modeling techniques seek to determine the expected amount of incapacity an infrastructure industry would experience given some disturbance in the networked industries. That is, given some scenario, these models would identify the reduction in capability on specific, individual nodes in the network. To measure the impact of individual node decay across the network, this paper proposes that the column summation of the damage vector **q** of each node *i* at each time *t*, which result from the probabilistic inoperabilities due to decay, be collected and compared to develop an ordered list of critical components over time. At each time *t*, the IIM equation is solved for the "destruction" of a single node and the column summation of the resulting **q**-vector is collected. The destruction of each node *i* at each time *t* then follows the probability distributions contained in the decay vector, **c***. Thus, for each *i* at each *t*:

$$\mathbf{q}^*_{\mathbf{i}}\,(\mathbf{t}) = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c}^*_{\mathbf{i}}\,(\mathbf{t}) \qquad (2.3)$$

where $\mathbf{c*_i(t)}$ is the vector where node i is inoperable, $c_i = 1$, and all other nodes j are fully operable $c_j = 0$ (such that $j \neq i$) at a time t. The Monte Carlo method allows for the deterministic calculation of each node i at each time t given the distributions contained in $\mathbf{c*(t)}$. To gather the component decay scores, the column summation of each $\mathbf{q*_i(t)}$ is stored as:

$$decay\_score_i(t) = \sum_{i=1}^{j} \mathbf{q*_i(t)} \tag{2.4}$$

The component decay scores from Equation 2.4 serve as a method to identify the effect of a decaying component i on the overall network of components for every time increment t.

2.6 An Interdependent, Simple Infrastructure Example

In this section, a six-node network is used to demonstrate the procedure for arriving at the infrastructure decay scores and the implications behind the results. The three components of this IIM variation are described, followed by the Monte Carlo algorithm, and finally a discussion of the results.

Figure 3 illustrates the simple, six-node network. This example shows a case with clear interdependencies of two infrastructures, water and electrical, servicing three facilities. The water infrastructure delivers water to the facilities by means of a pump house while the electrical infrastructure provides power for these facilities plus the pump house and the water tower. To facilitate the iterative matrix calculations, the node list of the systems must be ordered and this list is provided alongside the illustration.

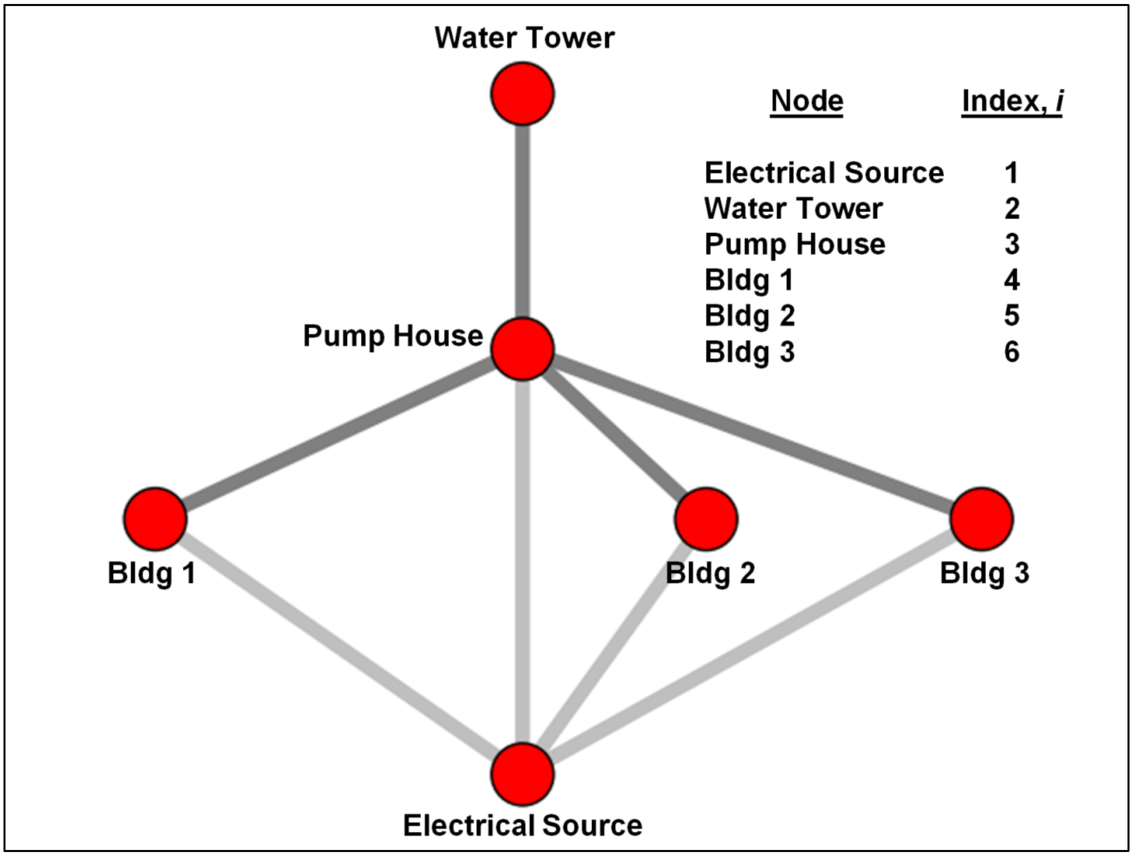

Figure 3. Illustrative six-node network of two infrastructures.

Given the Boolean assignments for the node interdependencies, the determination of the interdependency **A**-matrix is simply the transpose of the directional adjacency matrix, **A**(*D*), of the network. This is due to differences in matrix conventions between IIM modeling and graph theory. Using the ordered node list shown in Figure 3, **A**(*D*) and its transpose **A** are presented in Equations 2.5 and 2.6, respectively. As an illustration, element $a(D)_{13}$ for the **A**(*D*) matrix is equal to element a_{31} of the **A**-matrix, both of which equal 1. This indicates that the pump house is fully dependent on the electrical source operating. Should the electrical source fail, the full inoperability of the electrical source is transferred to the pump house.

$$\mathbf{A}(D) = \begin{pmatrix} 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{2.5}$$

$$\mathbf{A} = \mathbf{A}(D)^T = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \tag{2.6}$$

The development of the decay vector, **c***, is determined from collecting the decay distributions for each node in the system. For this example, the Weibull distribution, W(α, β), is used and parameterized such that all nodes exhibit a decay behavior, typically α > 1. Further, the distributions are varied such that the source nodes for electricity and the water tower have a mean time to failure of 18.6 years (α = 4, β = 20) and all other nodes (pump house and buildings) have a mean time to failure of 8.7 years (α = 3, β = 10). These parameters were chosen strictly for the illustrative purposes of this example and equation 2.7 presents the decay vector.

$$\mathbf{c}^* = \begin{pmatrix} W(4,20) \\ W(4,20) \\ W(3,10) \\ W(3,10) \\ W(3,10) \\ W(3,10) \end{pmatrix} \tag{2.7}$$

Monte Carlo simulation provides a feasible method for the deterministic calculations required to solve the IIM model yet account for the stochastic nature of component decay. With Monte Carlo simulation, the effect of the decay distributions for each node can be determined. The algorithm for such an operation involves a series of iterative steps where the results of the inoperability of each node is determined in the following manner. First, at time t, node 1 is sampled. Dependent on the probability of failure of node 1 at time t, this node has a Boolean value of either zero (operating) or one (failed). The IIM calculations are carried out with this node's sampled value and all other nodes set to zero. The resulting deterministic calculation results in a $\mathbf{q}_1(t)$ vector and this vector is column summed according to Equation 2.4. The column summation results in a sample decay score for node 1 at time t, or $decay\_score_1(t)$. The step is repeated for all other nodes at time t and repeated further for a predetermined number of iterations at time t. For this example, n = 1,000 was found to produce adequate convergence of solutions for each node at each time t. The resulting decay scores are averaged and thus, at each time t, each node has an average sample decay score. The algorithm is repeated for time steps of Δt = 0.1 years through 40 years. The results of the simulation are presented in Figure 4.

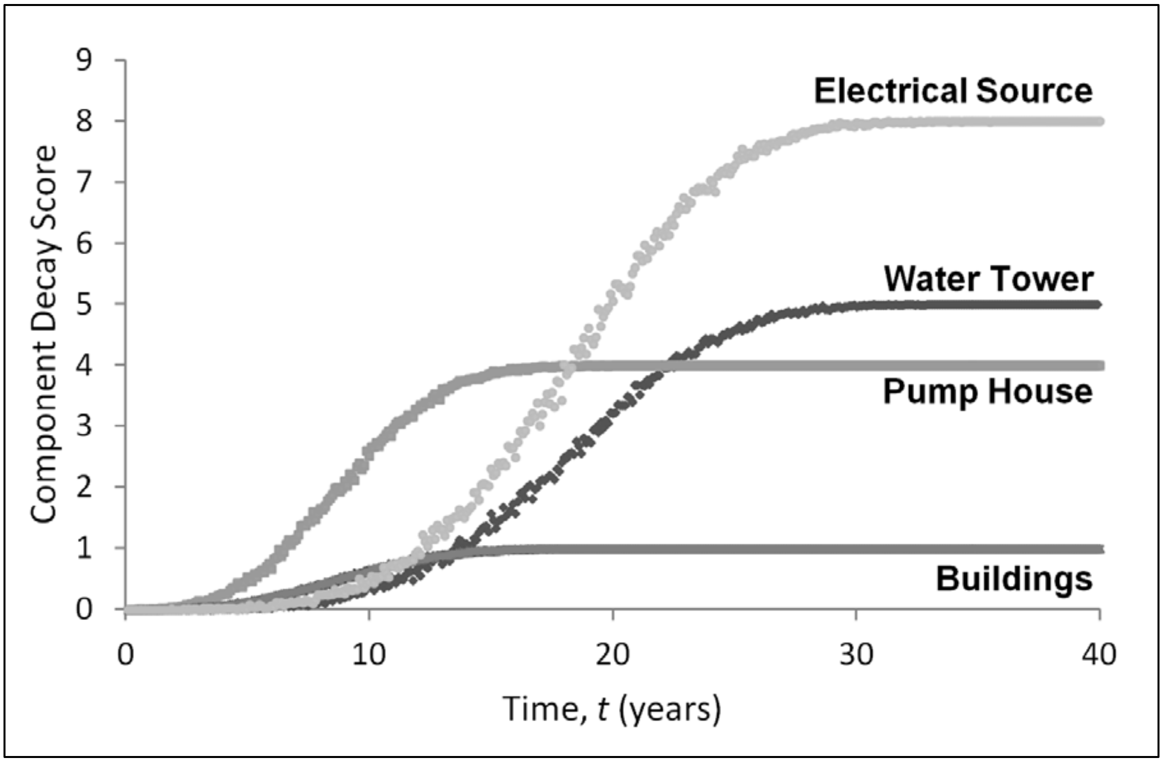

Figure 4. Simulation results from modified IIM.

There are several interesting implications to the IIM using the proposed simulation method. First, if one were to explore the inoperability effects of each node deterministically, it could be done simply by iterating down the list of nodes, “destroying” each node (i.e., $\mathbf{c}_i = 1$ for $i = 1 \ldots 6$), and summing the resulting damage vectors. Such a calculation would produce a bar graph (Figure 5) which is helpful in determining “critical nodes.” The illustration indicates that the system’s most critical components are the electrical source, water tower, and pump house. Indeed, the steady-state solution of the Monte Carlo simulation (i.e., Figure 4 at $t = 40.0$ years) indicate the same order for a criticality list.

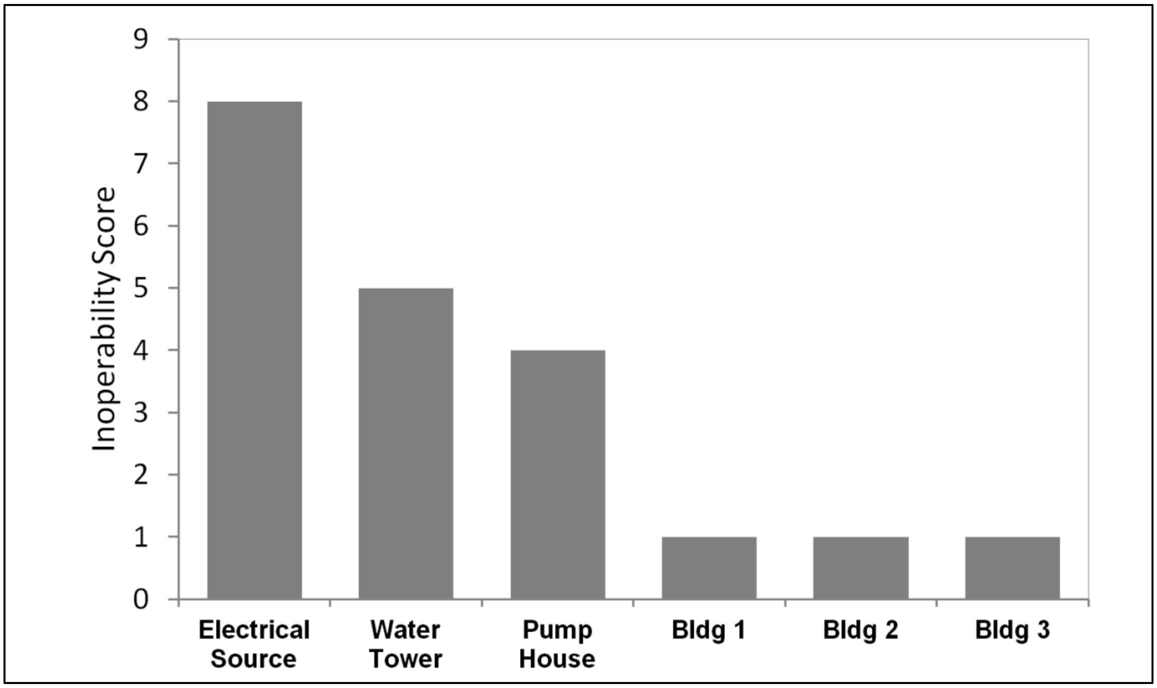

Figure 5. Bar graph of critical nodes from deterministic IIM.

Introduction of decay distributions, however, are able to capture the effect of time and component reliabilities on the overall system. For an asset manager with a 10 to 15 year outlook, Figure 4 reveals that attention must be paid to the pump house first, rather than the electricity and water sources. This is due to two factors. First, the reliability of the pump house less is than that of the two infrastrucutre sources. Second, the pump house's role as a "hub" of services for the network amplifies its criticality to the system. As the electrical source and the water tower serve as source nodes to the network, their outages result in cascading impacts across the entire network. The pump house serves as an intermediary in the network and so its outage also results in a cascade of failures, but with a partially operable network (albeit that the only two operating nodes are the sources in this example) and a lower criticality score in the long run. The deterministic, steady-state IIM captures this effect. The proposed model, however, is able to capture the dynamic effect of decay and emphasizes the importance of the pump house in the short-term. Insights such as this can lead asset managers to a better understanding of decay effects on their network and produce better policy and maintenance strategies.

Examples of such strategies include identifing the optimal times for repairs or defining a risk-based decision-making strategy. For example, one possible strategy could be to repair or replace the pump house before certain failure occuring somewhere around year 15. This would be an example of a preventive maintenance strategy and one based on a risk-averse approach to management. Alternatively, if accepting risk is part of a broader maintenance strategy, an asset manager might now better articulate the impact and the changing levels of impact over time should the asset management organization forgo maintenance and instead adopt a reactive maintenance strategy for the pump house or other nodes.

Finally, the component decay scores, $decay\_score_i(t)$, offer the magnitude of effects from an outage of a particular node. Whereas the electrical source scores eight points in the steady-state analysis (i.e., t = 40.0 years), the buildings only score one point. This is due to the directionality of the inoperabilities and the cascading effect that this modeling technique captures. An outage of the electrical source not only affects itself and the delivery of electricity to the pump house and buildings, but it also affects water delivery to the buildings since the pump house relies on electricity to operate. The simulation captures the cascading effects of an electrical outage whereby the buildings are inoperable twice (once for electricity outage and again for water outage). This cascading of inoperability accounts for the resulting high score for the electrical source. The buildings, on the other hand, contribute no inoperability to the system and therefore act as "sinks" in the network of nodes. Thus, their contribution of inoperability to the overall system is a result of their own outage and no other cascading effects.

This simple example illustrates the procedure in this modified version of a probabilistic IIM. The determination of the interdpendency matrix as strictly Boolean values simplifies one step of the IIM model. Inclusion of decay probability distributions admittedly adds a different complexity, but asset management organizations may already have such data or methods can be used to estimate such probabilities. Finally, Monte Carlo simulation allows for a practical means of solving this model. Taken together, asset managers have a means of understanding the effects of decay to the infrastructures they manage.

2.7 Conclusion

This paper presents a modifed version of the IIM which incorporates probalistic decay functions and Monte Carlo simulation to capture the dynmaic analysis of node inoperability. This is in contrast to the deterministic calculations of the original IIM. The four departures from the original model include limiting the scale of analysis to built infrastructure, using Boolean assignments for the interdependency **A**-matrix, introducing the decay vector **c***, and introducing the component decay score, $decay\_score_i(t)$, which is a column summation of calculated damage vectors over time. An example was presented that illustrated the computations and highlighted the insights to be gained from the method.

The framework in this paper helps asset managers understand the effects of component decay throughout their interdependent networks. In addition, several key findings are highlighted:

- Modeling in asset management requires quality data to support the modeling process
- The primary output of such a process must lead to thoughtful resource planning which supports strategic objectives
- Infrastructure interdependency analysis requires *both* a top-down and bottom-up system perspective be taken
- The interdependency **A**-matrix using Boolean assignments ignores the strength of connected system components, but the simplifications lead to a generalizable model and increase the potential for use
- The **c*** decay vector requires probabilistic failure distributions, i.e., decay curves, that do not readily exist for infrastructure assets

Given these findings, several opportunities for future research in the topics of infrastructure decay and interdependencies are apparent. For example, further exploration in engineering reliability may offer insight into how to estimate reliabilities for expansive networked systems typical of built infrastructures. As stated before, the collection of component-level decay data for these infrastructures presents a formidable challenge. As another example, one possible solution to dealing with the expansiveness of systems might be to identify the proper level of abstraction for modeling infrastructures. Developing methods and understanding the effect of such abstraction could be further studied. A final example of future research might be to explore multi-layer modeling as it is applied to the IIM. Currently, the IIM must model interdependent systems as a two-dimensional field of adjacent nodes. An IIM approach using a multi-layer, three-dimensional model may increase understanding of cascading effects between disparate infrastrucutures.

Infrastructure asset managers play an important role in society as they are charged with ensuring the consistent delivery of basic services. Conceptual overlaps with several academic and engineering fields have been demonstrated in this paper. Presented herein is a product of such an overlap and represents one possible method for asset managers in managing their infrastructure systems.

III. Multi-Layer Modeling for Interdependent Infrastructure Systems[2]

3.1 Introduction

Network analysis provides a powerful means of modeling and studying infrastructure system behavior. Many applications in recent years attempt to capture the behavior of interdependent infrastructure networks (Satumtira & Dueñas-Osorio, 2010). The modeling approaches are varied and some directly address the multi-layered nature of interdependent infrastructure systems. Examples of recent multi-layer modeling include Kurant and Thiran (2006) who explore topological differences between a physical layer (a road network) and corresponding logical layer (network of traffic flows). Buldyrev, Parshani, Paul, Stanley, and Havlin (2010) develop an interdependent network analysis framework based on an Italian power network and its supervisory control and data acquisition (SCADA) system network. Brummitt, D'Souza, and Leicht (2012) study the effect of changing interconnections between two distinct power grid networks. Critical infrastructure vulnerability assessment within the context of layered infrastructure systems was proposed by Johansson and Hassel (2010).

These works differ from other, single-layer network studies in their treatment of infrastructure systems. Rather than limiting the scope of their modeling to a single infrastructure type or characterizing multiple infrastructures as a single network, the works highlighted above maintain distinct infrastructure layers but relate these layers to one another through a mapping layer. They take on a multi-layer modeling paradigm that

[2] The contents of this chapter were independently submitted for publication by Valencia, Sitzabee, Bulutoglu, Colombi, and Thal to the *International Journal of Strategic Engineering Asset Management* on May 23, 2013.

is able to relate disparate infrastructure networks to each other. This paradigm necessitates the creation of an inter-layer which models the node connections from one layer to the next. Kurant and Thiran (2006) call their inter-layer a "mapping," Buldyrev et al. (2010) create the terminology "A $\leftrightarrow$ B links" to denote node connections from layer A to layer B, Brummitt, D'Souza, and Leicht (2012) use the term "interconnections," and Johansson and Hassel (2010) use the term "functional dependencies." Regardless of the terminology and the respective methodologies, these studies have in common the creation of an additional layer to capture inter-network connections from one layer to the next.

A multi-layer approach in the modeling of interconnected infrastructure systems is an intuitive approach for geographic information system (GIS) users. Church (2002) highlights that the use of data layers has a long history in mapping and cartography and is the basis of GIS analysis today. Layers in a GIS are a collection of data on entities which share common attributes and are stored together (Longley, Goodchild, Maguire, & Rhind, 2011). For example, the shape and location of lines for a water distribution system could be stored in a layer, the point locations and attributes of valves and pumps in another layer, and the facilities that the distribution system serves in yet another layer. Aggregating these together provides a single grouped layer which represents the water distribution network in its entirety. A GIS has the ability to store and present individual infrastructure systems and facilities as a single layer, albeit a layer of layers, because GIS uses geo-location as a common key in its relational data structure to link all the data sets together. Therefore, a GIS facilitates a multi-layer approach in the analysis of interdependent infrastructures.

This chapter proposes a method of analysis that takes advantage of the relational database structure of GISs to further study and identify the interdependencies in infrastructure systems. Based on the well known input-output inoperability model (IIM) developed by Haimes and Jiang (2001), we present a modification of the model which allows for the use of multiple adjacency matrices combined with "mapping" layers to represent a system of interdependent infrastructures. The remainder of this article is organized as follows. First, the IIM is briefly described with a discussion of its two primary limitations. Second, a case is made which outlines the suitability of a modified model in a GIS environment. Third, the proposed method of integrating aspects of the IIM and GIS data structures is introduced with a three-layer facilities example. Finally, the article concludes with significant findings, limitations, and possible extensions of the model.

3.2 Input-output Inoperability Model

For any network, topologies can be captured in the form of a simple two-dimensional matrix by recording node connections in an adjacency matrix (West, 2001). A pair of nodes connected by an edge are considered adjacent and variations to the adjacency matrix, such as edge weighting and directionality, can capture differences in adjacencies, such as connection strength, flow, and direction. Lewis (2009) asserts that adjacency matrix representation is an efficient and compact method for storing network topologies. Indeed, many studies utilize network adjacency matrices in studying infrastructure interdependencies. A well studied method is the input-output inoperability model and its extensions, developed by Haimes and others (Barker & Haimes, 2009; Crowther & Haimes, 2005; Haimes & Jiang, 2001; Haimes, 2009; Santos, 2008), which capture network interdependencies across a system of infrastructures. Based on the well known input-output (I/O) technique (Miller & Blair, 1985), the effect of a perturbation in one part of a networked system of infrastructures can be calculated for other parts of the system.

The IIM uses a network's topology in matrix form to understand this propagating effect in a system of infrastructures. Termed the "risk of inoperability," the IIM captures the risk of transferring "inoperation" from one node to a connected node through a modified adjacency matrix. In compact matrix form, the matrix notation of the IIM is:

$$\mathbf{q} = \mathbf{A} \cdot \mathbf{q} + \mathbf{c} \tag{3.1}$$

where **c**, the scenario vector, describes the disruption in the network. If the system being modeled has *n* number of nodes in its network, the size of column vector **c** is *n x 1*. Each entry in vector **c** is an inoperability value between 0 and 1, where zero denotes no inoperability, or fully operational, and one denotes complete inoperability, or fully damaged. Thus, a simulation modeling an event which completely destroys a particular node would enter a 1 at that node's position in vector **c** while all other entries in **c** would be a 0. A value in **c** between 0 and 1 indicates the percentage that a particular node is inoperable. The damage vector, **q**, describes the resulting damage of each node after application of the scenario vector, **c**. Much like the scenario vector **c**, **q** is sized *n x 1*, and each entry in **q** describes the inoperability after application of the scenario. Vector **q** is the vector of interest and represents the effect of the network perturbation.

At the core of the IIM is the interdependency matrix, **A**, which represents the network topology and the risks of transferring inoperabilities within the network. Matrix **A** is sized *n x n* and contains entries between 0 and 1, where any entry greater than 0 denotes a directional link between two nodes. For any entry a_{ij}, a 0 would indicate that there is no risk of transferring inoperability between node *j* and node *i*. Any entry greater than 0 denotes that node *j* has some probability of transferring its inoperability to node *i*. It is interesting to note that **A** is a modified adjacency matrix in that the matrix entries are continuous values from 0 to 1, rather than Boolean, and the convention of directionality is reversed. For example, if a_{ij} = 0.35, this entry indicates that the complete malfunction, or inoperability, of node *j* would result in 35% reduced operation of node *i*. To solve Equation 3.1, the operation is simply:

$$\mathbf{q} = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c} \tag{3.2}$$

where **I** is the *n x n* identity matrix and the inversion of (**I – A**) is necessary for solving vector **q**. Haimes and Jiang (2001) and Haimes (2009) provide further details on the derivation of the IIM.

Although mathematically sound, the IIM suffers from two challenges involving matrix **A**. First, the development of the inoperability **A**-matrix is a challenge because of the level of abstraction chosen for the networks to be studied. For example, the Bureau of Economic Analysis (BEA) is commonly cited as a data source in the development of the **A**-matrix. The BEA data contains inputs and outputs for entire economic sectors, so an individual node in this style of modeling represents an entire infrastructure sector with no ability to decompose each sector into its own network. IIM analysis occurs at a high level of abstraction, taking a top-down view, and precludes the study of technical infrastructures at the component level, or bottom-up view. In their seminal work, Haimes and Jiang (2001) highlight that data collection for the **A**-matrix is indeed a significant challenge and list “pointers” to overcome this challenge.

Second, matrix algebra operations utilized in the IIM must be executed on two-dimensional matrices. Therefore, modeling of multiple infrastructure systems must be conducted with a single, inherently large network. Although multi-dimensional matrix operations have been defined (Solo, 2010 a-f), application of these methods is not possible due to dimensionality constraints when carrying out multi-dimensional matrix algebra. Specifically, the IIM requires square matrices in defining its **A** matrix, a constraint that might not be possible when defining interdependencies between infrastructure layers since each layer most likely has differing numbers of nodes. To model separate, yet interconnected infrastructure systems, the IIM must thus represent a system of infrastructures as a single network.

With these two sets of challenges, the IIM is limited in its analysis of multiple, interdependent networks to a single system and characterizes individual infrastructures networks within that system as single nodes. In this paper, we argue that these challenges can be overcome. The use of GIS addresses the first challenge of network abstraction. In the last two decades, GIS has undergone an increase in use and availability (Longley et al., 2011). The widespread availability of data has driven the creation of data models specific for network analysis and these methods can be applied to geospatial asset management data. To address the second challenge of matrix algebra operations on a multi-layered system, a modification to the IIM procedure will allow for these calculations to be carried out. Using GIS and a multi-layer framework will allow for the extension of the IIM model to built infrastructure systems.

3.3 Network Analysis and GIS

Network analysis has evolved over the last decade such that specific GIS data structures and utilities are commonly available in off-the-shelf software packages (Curtain, 2007). These GIS network data models are significant as they provide the ability to merge the spatial representation of real-world features with topological relationships of the underlying network (Lwin & Murayama, 2012). Therefore, the mathematics of graph theory and network analysis can be applied to GIS datasets. The ability to store, retrieve, process, and display spatial and attribute data provides a GIS the potential to execute a wide range of network analysis studies.

However, Curtin (2007) finds that most network analysis methods are limited to transportation infrastructures and that these methods are simply a variant of a classical graph theory problem, the shortest path problem, which seeks the shortest route for a node pair in a connected network. The variants of the shortest path include routing problems, facility location-allocation analyses, closest facility problems, and origin-destination cost analyses. Indeed, one common GIS software package, ArcGIS supplied by the Environmental Systems Research Institute (ESRI), offers a fully integrated network analysis module that solves these exact problems (ESRI, 2013). Other researchers share Curtin's view. Lwin and Murayama (2012) highlight the same problem sets as common functions in a GIS. Fischer (2004) explores three specific network problems, namely the travelling salesman problem, vehicle routing problems, and constrained shortest path problems. Although they have different objectives, these GIS network methods remain variants of the shortest path problem.

For infrastructures other than transportation, solutions to the shortest path problem provide limited utility in the management, operation, and maintenance of technical infrastructure systems. An example of an infrastructure network simulation and analysis method available in a GIS is the utility tracing function. The tracing function highlights the networked path of connections from one node to another and can show the set of disconnected nodes if flow is blocked. Another example is the flow analyses function which provides the flow direction of a utility system given a set of source and sink nodes. Although insightful, these two functions remain within the realm of the shortest path problem. Network problems found in the infrastructure literature go beyond finding the shortest path and include network risk and vulnerability problems, critical node and link analysis, identifying cascading effects across a network, and indentifying cascading effects across interdependent networks (Haimes, 2009; Lewis, 2006; Lewis, 2009). Currently, these types of studies frame their network problems in a purely topological context without regard to spatial attributes; therefore, these types of studies are not well represented in the GIS literature.

A primary benefit of a GIS is its ability to aggregate such data as these systems are based on relational data models. Navathe (1992) reviews the evolution of data modeling and highlights that the widespread use of these models is due to their basis in the mathematical definitions of sets and relations. The underlying mathematics of relational data modeling allows for the comparison of large "sets" of data. Entire tables become arguments for operations such as joins, unions, intersections, etc., and this allows for powerful data analysis techniques. Navathe (1992) further states that relational data models are suited for addressing common issues such as data fragmentation, redundancy, and distributed operations; additionally, Halfawy (2010) suggests that many infrastructure management organizational environments are pre-disposed to perpetuate these data integrity issues. A GIS is a powerful tool as it will not only aggregate data employing data integrity constraints, but it will do so by using location as a referential key. Thus, for example, the data composing three infrastructure layers need not be contained within one GIS but could be independent databases with a GIS linking these data according to location. In fact, infrastructure data is often kept in a Maintenance Management System (MMS) that is compatible with a GIS software package. This allows users to keep various data current and accurate while allowing for easy integration with other systems.

The prevalence of GIS as a central element in an asset management strategy allows for the possibility to relate the spatial attributes of infrastructure assets to a network analysis problem. Curtain (2007) suggests that the network analysis in GIS presents many opportunities to expand the field's analytic capability and we present an analysis model in response to that challenge. Additionally, we assume that organizations already possess, or have the ability to create, topologically correct network models from their GIS data. Possessing such data is a significant assumption and we do not address this issue in depth; given a "topologically clean" dataset though, directional adjacency matrices can easily be extracted. The following section presents a multi-layer interdependency framework based on the GIS data structure to enhance network analysis beyond network shortest path problems.

3.4 An Infrastructure Network Example

Given a network layer with n nodes, the directional adjacency matrix **A***(D)* is an n x n matrix with entries of m_{ij}. Boolean assignments for each entry are used due to its simplicity in expressing the existence of an edge, or connection, between nodes. An entry of $m_{ij} = 1$ indicates an adjacency from the node at row index (i) to the node at column index (j). An entry of $m_{ij} = 0$ indicates no adjacency between the two nodes at the two indices. **A***(D)* is not normally symmetric and so $m_{ij} \neq m_{ji}$ will most often hold true. Additionally, $m_{ii} = 0$ will hold for every node i since infrastructure systems do not contain nodes with self loops, that is, infrastructures do not contain components that are connected to itself. The directional adjacency matrix is a simple representation of a more complex network.

Consider the following infrastructure system in Figure 6. The layered network captures a three-layer infrastructure system of heating, water, and electrical distribution systems consisting of six facilities. For the heating infrastructure, the system distributes hot water for facility heating to Facilities 1 and 2. In the water infrastructure, the water tower supplies water to the pump house which enables the transport of water to Facilities 1 and 2 and the heating plant. Finally, for the electrical infrastructure, the substation is considered the source of electricity and provides power to four facilities: Facilities 1 and 2, the pump house, and the heat plant.

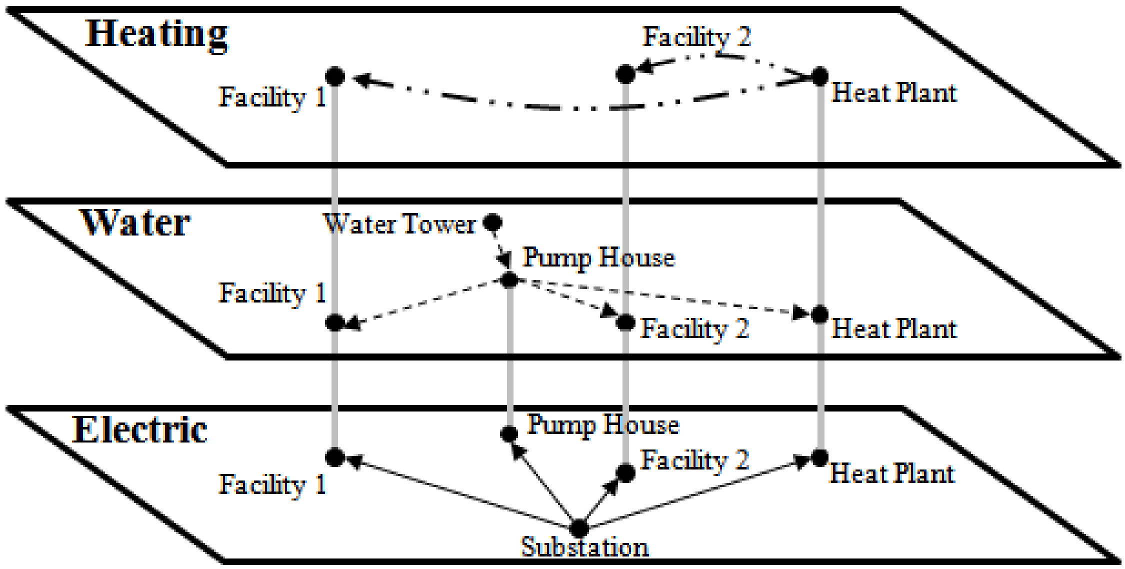

Figure 6. A three layer infrastructure system.

3.4.1 Analysis with the IIM.

Recall that the IIM is used to determine a networked system's inoperability given a scenario that introduces a perturbation in the system. Such a disturbance could be the reduced or total incapacity of some node in the system. If the three infrastructure systems in Figure 6 are modeled as a single network, then the original IIM can be applied. Supposing that the risk of inoperability for each interacting node is assumed to be 1, that is, receiving nodes are 100% reliant on their source nodes, then the IIM's interdependency matrix, **A**, is simply a transpose of the network's directional adjacency matrix, ***A(D)***:

$$\mathbf{A} = \mathbf{A}(D)^T \tag{3.3}$$

If we use the **c**-vector to model a scenario where the electrical substation is 100% inoperable, we have the following parameters for an IIM analysis:

$$\mathbf{A}(D) = \begin{array}{r} \\ \text{Water Tower} \\ \text{Pump House} \\ \text{Substation} \\ \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{array} \begin{array}{c} \begin{array}{cccccc} \rotatebox{90}{Water Tower} & \rotatebox{90}{Pump House} & \rotatebox{90}{Substation} & \rotatebox{90}{Heat Plant} & \rotatebox{90}{Facility 1} & \rotatebox{90}{Facility 2} \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \quad \mathbf{c} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{array}{l} \text{Water Tower} \\ \text{Pump House} \\ \text{Substation} \\ \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{array} \quad \mathbf{I} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.4)$$

Solving Equation 3.2, but with $\mathbf{A} = \mathbf{A}(D)^T$ as in Eq. (3.3), yields the following:

$$\mathbf{q} = [\mathbf{I} - \mathbf{A(D)}^T]^{-1} \cdot \mathbf{c} \qquad \rightarrow \qquad \mathbf{q} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 2 \\ 4 \\ 4 \end{bmatrix} \begin{array}{l} \text{Water Tower} \\ \text{Pump House} \\ \text{Substation} \\ \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{array} \qquad (3.5)$$

Vector **q**, the damage vector, can be interpreted as follows. From top to bottom, we find that the water tower is not affected by the complete inoperability of the substation. The pump house, however, results in 100% inoperability as a result of the non-working substation. The substation is also 100% inoperable as a result of the scenario vector **c**. The heat plant results in 2 x 100% inoperability because the substation no longer provides electricity to the heat plant nor does the plant receive water from the inoperable pump house. The two facilities are 4 x 100% inoperable as a result of accumulating inoperabilities from the pump house (100%), substation (100%), and heat plant (200%). One interpretation of vector **q** might be that any node whose value is greater than 1 should be considered 100% inoperable as a result of the scenario vector **c** (Haimes, 2009). The results indicate that all nodes, except the water tower, are completely inoperable for the given scenario. Another interpretation could use the rank order of the results to determine system vulnerabilities as part of a risk assessment strategy (Crowther & Haimes, 2005). The resulting vector **q** from this IIM analysis is the basis of comparison for the proposed multi-layer matrix model.

3.4.2 A Multi-Layer Model.

The term "layers" is used slightly differently in a GIS setting than in the proposed model. In a GIS, the three infrastructures shown would consist of several data layers. A data layer is analogous to a dataset where features with like attributes are stored together (Longley et al., 2011). For example, a facilities layer would store geographic location, geographic extent, and additional attributes such as building title, size, population, etc. In the present example, a facilities data layer would consist of six entries, one for each facility, and the associated attributes for each facility. For each infrastructure system, two data layers are needed. The first layer would consist of the edges of the networked system such as water piping, electrical, or heating distribution lines. The other layer would consist of the junctions and endpoints of these lines. Therefore, a GIS setting for this problem might require seven distinct data layers although there are only three infrastructure layers to model.

In a network analysis model such as the IIM, modeling the system is limited to modeling only a single network. One approach could be to model the system as three discrete layers of water, electricity, and heating and then analyze them separately. However, this fragmented approach would not capture network interdependencies. Conversely, the system could be modeled as a "large" single infrastructure network, which would be more in line with the traditional IIM, but this method introduces two other difficulties.

The first difficulty arises in attempting to discern network topology. If multiple systems are aggregated and displayed as a single GIS layer, the determination of network connections becomes problematic when lines from differing infrastructures cross. Basic snapping and crossing rules used to automate the process of constructing a network may inadvertently create junctions between two lines where one does not exist or ignore a junction where one should exist. Therefore, geographic locations that are particularly dense with infrastructure components would be difficult to accurately model. Second, the inverse matrix operation of Equation 3.2 may not be possible if cycles or loops exist in the network. This is problematic as the nature of interdependent infrastructures necessarily means that these loops exist somewhere in the network. In fact, some infrastructures are specifically designed in a looped arrangement to facilitate continued service should a break occur which necessitates the isolation of a portion of the loop. This finding and a solution to it are illustrated as a special case to the model proposed.

Given these challenges in interdependency modeling, we propose a multi-layer modeling approach which, alongside the adjacency matrices for each infrastructure layer, creates mapping layers to capture inter-layer interdependencies. These mapping layers are similar to the inter-layer mappings found in Kurant and Thiran (2006), Buldyrev et al. (2010), Brummitt et al. (2012), and Johansson and Hassel (2010). By using a multi-layer modeling approach that employs mapping layers between infrastructures, the proposed model: (1) leverages the power of a GIS in relating independent infrastructure data layers,

(2) relieves some potential difficulties associated with discerning network topology, and (3) eliminates a source of potential cycles in the system.

Using the infrastructure system illustrated in Figure 6, the needed matrices for describing the proposed multi-layer model are displayed in Figure 7. The top level matrix, **M**, is the multi-layer collection of each matrix describing the system of infrastructures. Each of the matrices in **M** are directional adjacency matrices and use Boolean assignments to capture these adjacencies. Thus, the water adjacency matrix, $\mathbf{A}(D)_{water}$, captures the water network dependencies from the tower to the pump house and then the pump house to the facilities and heating plant. Likewise, the electrical and heating adjacency matrices, $\mathbf{A}(D)_{electrical}$ and $\mathbf{A}(D)_{heating}$, respectively, capture the dependencies for their distribution systems.

To capture inter-layer interdependencies, the mapping layers of $\mathbf{I}_{electric \rightarrow water}$ and $\mathbf{I}_{water \rightarrow heating}$ are composed of nodes from interacting layers. Similar to the adjacency matrix convention, nodes listed as row indices are "from" nodes which transfer interdependencies to nodes listed as column indices. Again, an entry of $m_{ij} = 1$ indicates an adjacency between node i and node j while $m_{ij} = 0$ indicates no adjacency. Furthermore, mapping layers for all layer interactions need not be created. The iterative procedure proposed below permits the capturing of interdependency effects as long as the multi-layer matrix **M** lists each infrastructure layer once with mapping layers sandwiched between theses infrastructures. Therefore, an $\mathbf{I}_{electric \rightarrow water}$ mapping layer is not created for the example infrastructure.

$$\mathbf{M} = \begin{bmatrix} \mathbf{A(D)}_{heat} \\ \mathbf{I}_{water \rightarrow heat} \\ \mathbf{A(D)}_{water} \\ \mathbf{I}_{electric \rightarrow water} \\ \mathbf{A(D)}_{electric} \end{bmatrix}$$

$$\mathbf{A(D)}_{water} = \begin{array}{r} \\ \text{Water Tower} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{array} \begin{array}{ccccc} \text{Water Tower} & \text{Pump House} & \text{Facility 1} & \text{Facility 2} & \text{Heat Plant} \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array}$$

$$\mathbf{A(D)}_{electric} = \begin{array}{r} \\ \text{Substation} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{array} \begin{array}{ccccc} \text{Substation} & \text{Pump House} & \text{Facility 1} & \text{Facility 2} & \text{Heat Plant} \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array}$$

$$\mathbf{A(D)}_{heating} = \begin{array}{r} \\ \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{array} \begin{array}{ccc} \text{Heat Plant} & \text{Facility 1} & \text{Facility 2} \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array}$$

$$\mathbf{I}_{electric \rightarrow water} = \begin{array}{r} \\ \text{Substation} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{array} \begin{array}{ccccc} \text{Water Tower} & \text{Pump House} & \text{Facility 1} & \text{Facility 2} & \text{Heat Plant} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{array}$$

$$\mathbf{I}_{water \rightarrow heating} = \begin{array}{r} \\ \text{Water Tower} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{array} \begin{array}{ccc} \text{Heat Plant} & \text{Facility 1} & \text{Facility 2} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{array}$$

Figure 7. System of matrices representing the example three infrastructure network.

The system of matrices in Figure 7 represents the network topologies for the interdependent, three-system infrastructure network. The first feature of the multi-layer model is its leveraging of a GIS's power through relating data on each system, which may exist independently, based solely on location. Further, the multi-layer model may mitigate some problems of identifying network topology if the network connections of each system are maintained independently. The last benefit of the multi-layer model, elimination of potential cycles, is illustrated through the following proposed algorithm.

3.4.3 An Algorithm to Solve the Multi-Layer Network Problem.

Given the layered data structure of most GIS platforms, a multi-layered framework is an intuitive approach for GIS users in the study of network interdependencies. The following section outlines a procedure that utilizes such a framework as applied to the simple infrastructure example illustrated and modeled in Figures 6 and 7. The algorithm applies the IIM to individual infrastructure networks in sequence, with an intermittent step for capturing and passing interdependency effects between infrastructures. Figure 8 displays this iterative procedure.

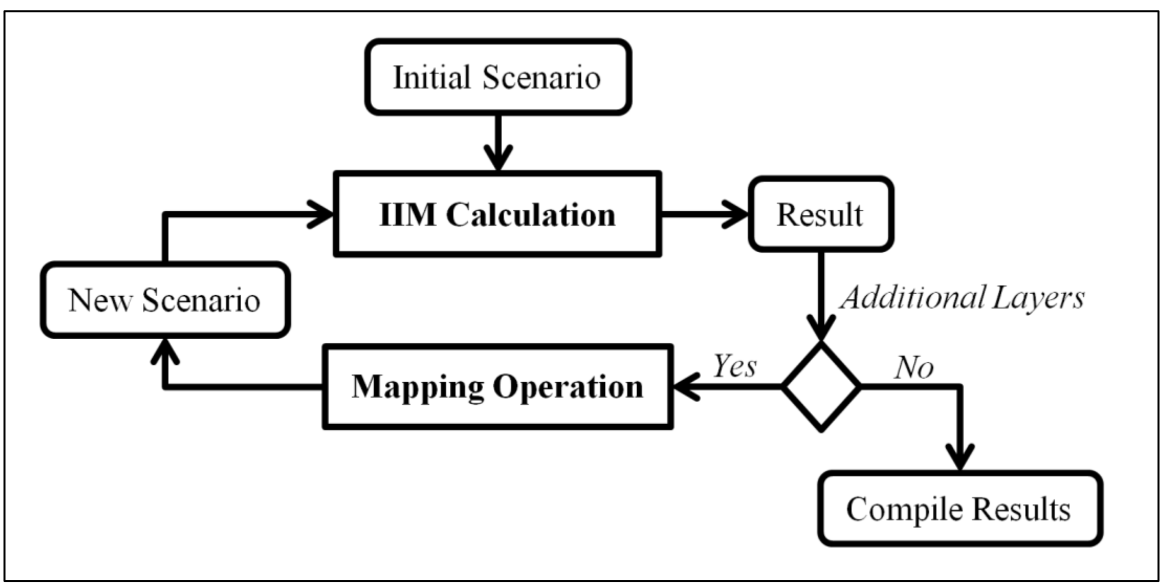

Figure 8. Diagram for iterative multi-layer network problem.

3.4.3.1 *Step 1 – IIM Calculation.*

Given the scenario vector **c** in Equation 3.4, the initial layer to analyze must contain a node affected by vector **c**. Since the scenario involves a node from the electrical infrastructure, Equation 3.2 is solved for the electrical infrastructure only. As this operation involves only the set of nodes that compose the electric infrastructure, scenario **c** is reduced to $\mathbf{c}_{electric}$. Equation 3.6 is the initial scenario.

$$\mathbf{c}_{electric} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \text{Substation} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{matrix} \tag{3.6}$$

The resulting operation to determine $\mathbf{q}_{electric}$ is Equation 3.7.

$$\mathbf{q}_{electric} = \left[\mathbf{I} - \mathbf{A(D)}_{electric}{}^{T} \right]^{-1} \bullet \mathbf{c}_{electric} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{matrix} \text{Substation} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{matrix} \tag{3.7}$$

As in Equation 3.5, the transpose of $\mathbf{A}(D)_{electrical}$ is taken to conform with the original IIM's **A-**matrix convention. The result of the operation is $\mathbf{q}_{electric}$ and indicates that all nodes of the electrical infrastructure layer are 100% inoperable as a result of the scenario **c**.

3.4.3.2 *Step 2 – Mapping Operation.*

As there are remaining layers to analyze, a subsequent layer for the mapping operation is chosen. This selection is based on the remaining nodes that are affected by scenario **c**. If scenario **c** contains additional nodes affected, but not yet analyzed, then the layer which contains those nodes is chosen. In the present example, there are no nodes remaining and the selection is arbitrary. Equation 3.8 presents the mapping operation to derive a new scenario vector,

$$\mathbf{c}_{electric \rightarrow water} = \mathbf{I}_{electric \rightarrow water}{}^{T} \cdot \mathbf{q}_{electric} + \mathbf{c}_{water} \tag{3.8}$$

where $\mathbf{I}_{electric \rightarrow water}$ is taken from the system of equations in Figure 7 and transposed, $\mathbf{q}_{electric}$ is taken from Equation 3.7, and $\mathbf{c}_{water}$ is the subset of nodes from the scenario vector **c** that are part of the water infrastructure. Transposing $\mathbf{I}_{electric \rightarrow water}$ is necessary to facilitate the matrix multiplication to the $\mathbf{q}_{electric}$ vector. Equation 3.9 shows $\mathbf{c}_{water}$.

$$\mathbf{c}_{water} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \text{Water Tower} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{matrix} \tag{3.9}$$

With Equation 3.8, we now have $\mathbf{c}_{electric \rightarrow water}$ (see Equation 3.10) which describes the scenario vector to apply to the next infrastructure analysis. This vector is significant as it accounts for both the original inoperabilities from scenario vector **c** and any calculated inoperabilities from the previous step's infrastructure analysis. The operation presented in Equation 3.8 maps inter-layer dependendencies and allows for the multi-layer modeling.

$$\mathbf{c}_{electric \rightarrow water} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{matrix} \text{Water Tower} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{matrix} \tag{3.10}$$

3.4.3.3 *Step 3 – Subsequent IIM Calculation.*

Using the new scenario vector $\mathbf{c}_{electric \rightarrow water}$, Equation 3.2 is solved for the appropriate infrastructure layer. In the present example, this is the water infrastructure layer.

$$\mathbf{q}_{water} = \left[\mathbf{I} - \mathbf{A(D)}_{water}{}^{T}\right]^{-1} \bullet \mathbf{c}_{electric \rightarrow water} = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 2 \\ 2 \end{bmatrix} \begin{matrix} \text{Water Tower} \\ \text{Pump House} \\ \text{Facility 1} \\ \text{Facility 2} \\ \text{Heat Plant} \end{matrix} \quad (3.11)$$

3.4.3.4 Step 4 – Repeat Steps 2 and 3 for Remaining Layers.

For the present example, only the heating infrastructure layer remains. Therefore,

$$\mathbf{c}_{water \rightarrow heating} = \mathbf{I}_{water \rightarrow heating}{}^{T} \cdot \mathbf{q}_{water} + \mathbf{c}_{heating} = \begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} \begin{matrix} \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{matrix} \quad (3.12)$$

where $\mathbf{I}_{water \rightarrow heating}$ is from Figure 7 and transposed, $\mathbf{q}_{water}$ is from Equation 3.11, and $\mathbf{c}_{heating}$ is the zero vector for the three nodes that comprise the heating infrastructure layer. The final iteration results in:

$$\mathbf{q}_{heating} = \left[\mathbf{I} - \mathbf{A(D)}_{heating}{}^{T}\right]^{-1} \bullet \mathbf{c}_{water \rightarrow heating} = \begin{bmatrix} 2 \\ 4 \\ 4 \end{bmatrix} \begin{matrix} \text{Heat Plant} \\ \text{Facility 1} \\ \text{Facility 2} \end{matrix} \quad (3.13)$$

3.4.3.5 Step 5 – Compile Final Results.

The final results of the analysis should follow the results from the two-dimensional matrix analysis from Equation 3.5. Collecting the **q**-vectors from the multi-dimensional analysis leads to the series of vectors in Equation 3.14, and collecting the maximum scalar value for each node results in $\mathbf{q}_{\text{final}}$ for Equation 3.15.

$$\mathbf{q}_{electric} = \begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix}\begin{array}{l}\text{Substation}\\\text{Pump House}\\\text{Facility 1}\\\text{Facility 2}\\\text{Heat Plant}\end{array} \quad \mathbf{q}_{water} = \begin{bmatrix}0\\1\\2\\2\\2\end{bmatrix}\begin{array}{l}\text{Water Tower}\\\text{Pump House}\\\text{Facility 1}\\\text{Facility 2}\\\text{Heat Plant}\end{array} \quad \mathbf{q}_{heating} = \begin{bmatrix}2\\4\\4\end{bmatrix}\begin{array}{l}\text{Heat Plant}\\\text{Facility 1}\\\text{Facility 2}\end{array} \tag{3.14}$$

$$\mathbf{q}_{final} = \mathbf{q} = \begin{bmatrix}0\\1\\1\\2\\4\\4\end{bmatrix}\begin{array}{l}\text{Water Tower}\\\text{Pump House}\\\text{Substation}\\\text{Heat Plant}\\\text{Facility 1}\\\text{Facility 2}\end{array} \tag{3.15}$$

The results in Equation 3.15 show that the final damage vector, $\mathbf{q}_{final}$, matches the results of the IIM calculations from Equation 3.5 and demonstrates that the proposed multi-layer method transfers inoperabilities using layered data.

3.5 Results and Findings

The proposed approach is significant in several ways. First, the results of $\mathbf{q}_{final}$ can be applied to take advantage of the visual display functions of a GIS. The cartograph in Figure 9 colors each facility based on the coding derived from $\mathbf{q}_{final}$. By communicating the results visually, the method presented now becomes a valuable tool to concisely relay the system's needs for maintenance, additional redundancy, or areas of high risk. Further, given the vastness of infrastructures and the ability of a GIS to store or integrate data, the method can easily be used to display interoperability information on a grander scale. Therefore, the method is generalizable for larger and more complex systems.

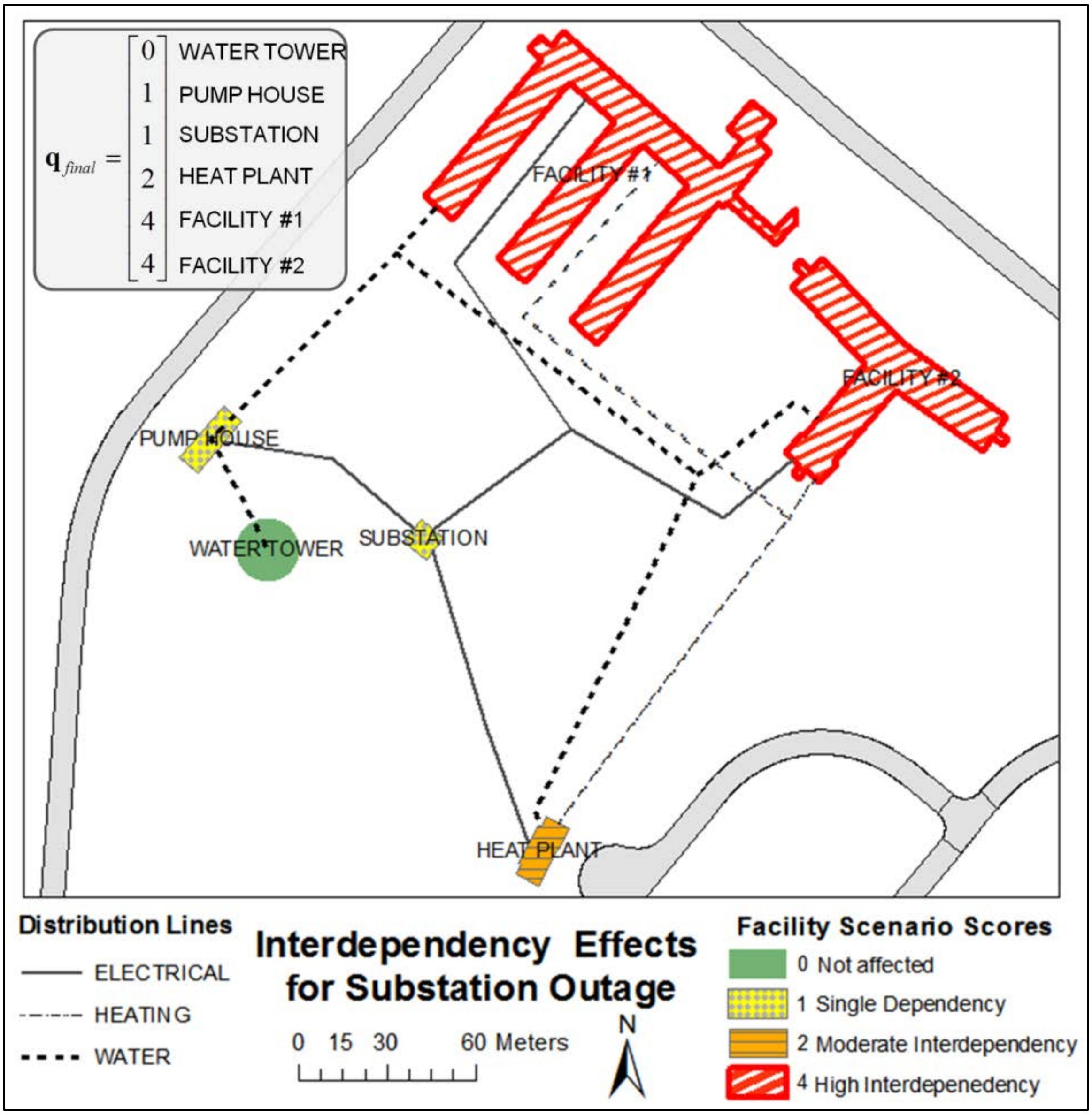

Figure 9. Example cartograph for results of system simulation with substation outage.

Second, the original formulation of the IIM, as well as subsequent studies using the model, relied heavily on economic databases to determine the inoperability matrix. With advances in GIS coupled with its wide spread use by infrastructure asset managers in inventorying and locating their assets, data is readily accessible which contain the topology of built infrastructure networks. Therefore, network analysis can be conducted at the component level of infrastructure systems rather than abstracted at high levels, such as in the original IIM. Modeling and analysis at component levels allows for greater understanding of the system and associated interdependency effects.

Third, the multi-layer framework of the model abolishes the need for a single, two dimensional matrix and the “large” network that accompanies it. Rather, multiple matrices are employed in defining the network as discrete layers, and this allows for network modeling according to infrastructure type. The infrastructures are tied together with mapping layers capturing interdependent relationships. Such a framework acknowledges the many layers of complex infrastructure networks (Amin, 2002) and makes use of the layered data structure common in GIS platforms. The proposed model provides a way to aggregate layers should infrastructure data be fragmented or siloed across different organizations, a common occurrence in infrastructure management (Halfawy, 2010; Rasdorf et al., 2009; Shen et al., 2010).

Fourth, the multi-layer framework relieves some difficulty in discerning network topology. Digitization processes of infrastructure assets may not accurately capture network topology or, in some cases, spatial data may not contain any topological relationships (i.e., the “spaghetti” data model). In fact, Figure 9 illustrates part of this problem where the visual representation is a perplexing jumble of distribution lines for the simple example. Although tools exist that automate the calculation of topologies, the process is generally inefficient (Curtain, 2007) and often results in errors. Basic spatial adjustment commands such as snapping and crossing rules may result in unintended junctions or omission of junctions. The proposed method emphasizes modeling within individual infrastructures and reduces the possibility of errors since the set of edges and nodes an analyst must model at a single time is reduced. A more accurate representation of the infrastructure results which leads to more sound modeling and analysis.

Finally, the proposed model provides a solution to the problem of cycles and loops. The core operation of matrix inversion, $(\mathbf{I} - \mathbf{A})^{-1}$, may not be possible due to the existence of cycles and loops which may create singular matrices. For instance, consider Figure 10(a) which depicts a looped infrastructure. $(\mathbf{I} - \mathbf{A})$ creates a singular matrix for which the inversion does not exist. Therefore, the calculation of Equation 3.2 cannot be carried out. As another example, Figure 10(b) demonstrates the example infrastructure as a single network with a modification to include an edge from the heat plant to the substation. This added edge forms cycles within the example system and application of the IIM method to this network model results in a negative determinant for $(\mathbf{I} - \mathbf{A})$. Negative values appear in the $\mathbf{q}$ vector and these inoperability values have no immediate interpretation.

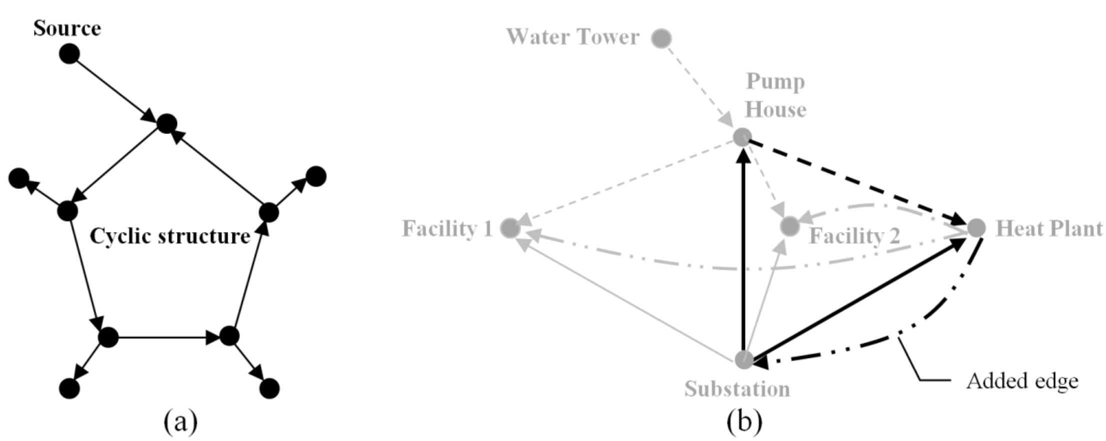

Figure 10. Networks with cycles are indeterminate with the IIM. (a) A generic looped infrastructure. (b) The example system with an added edge now contains cycles.

To solve both cases, elimination of cycles and loops is necessary. In the former case, modeling the looped system acyclically, as in Figure 11(a), eliminates these loops. For the latter case, the proposed multi-layer model and accompanying algorithm eliminates the effect of the existing cycle. The model decomposes Figure 10(b) into individual, layered infrastructures and reveals in Figure 11(b) that the added edge in the heating layer no longer results in a cycle. The proposed algorithm performs the matrix inversions on acyclic systems, transfers results through the mapping layers, returns an interpretable **q**-vector, and therefore permits interdependency analysis on multi-layered infrastructure systems.

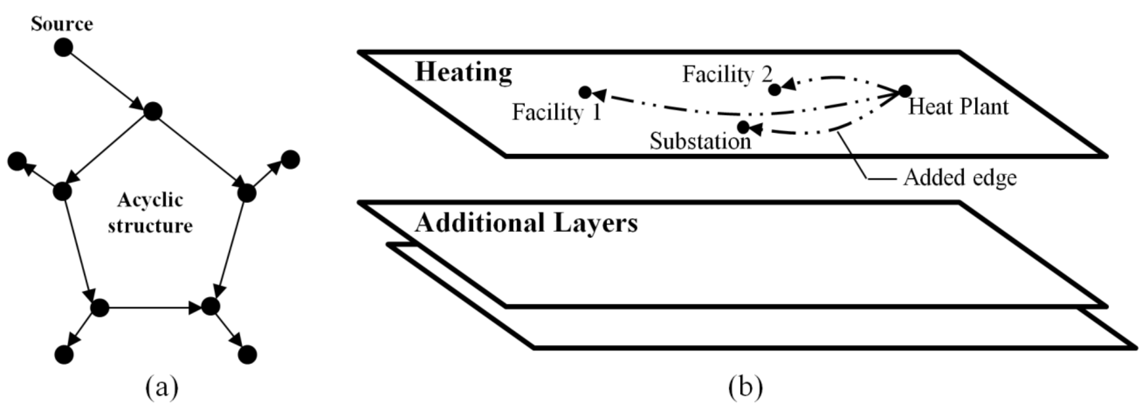

Figure 11. Modeling networks acyclically.
(a) An acyclic looped infrastructure. (b) Decomposition of the example problem reveals branched networks.

3.6 Conclusion

In this paper, we present a network analysis method for the modeling and study of infrastructure system behavior. Rather than limiting the scope of the modeling to a single infrastructure network, the model maintains distinct infrastructure layers and uses a mapping a layer to capture network interdependencies within the system. Given that network analysis in GISs are mostly limited to shortest path problems, the method in this paper offers an alternative analysis technique of infrastructures outside of finding the shortest path. In addition, several key findings are presented.

- Coupling GIS with the modeling method provides a powerful tool in describing network interdependencies
- GIS allows for interoperability network analysis to be conducted at the system component level rather than abstracting to higher levels, as in many IIM studies
- The model's multi-layer framework abolishes the need to create a single, "large" network and leverages the layered data model of a GIS to aggregate infrastructure data
- The model's multi-layer framework allows for more accurate modeling of network topology
- The model provides a solution to the problem of matrix inversion when cycles and loops are present

Future research includes integrating this model as a tightly coupled analysis module within a GIS software platform. Currently, shortest path solvers are provided within common GIS packages and development of a tool to easily conduct interdependency analysis will enhance the network analysis capabilities of a GIS. Second, the visual representation of interdependency modeling could be further explored as a GIS is a powerful visual tool that communicates its findings via annotated maps. Third, the model could be extended to explore non-Boolean representation of network adjacencies. Such an extension would explore the effect of representing differing connection strengths through percentages or weighted edges. Finally, the proposed model and example problem largely address physical interdependencies and do not explore the other dimensions of interdependency as defined by Rinaldi, Peerenboom, and Kelly (2001). The interdependency types of logical, cyber, and geographic could also be explored with the proposed method.

IV. Modeling Interdependent Infrastructures in Asset Management with the Input-output Inoperability Model[3]

4.1 Introduction

Infrastructure systems provide the basic underpinnings of modern society by ensuring essential goods and services are delivered to the people they serve. These systems are typically ignored and taken for granted by the public until there is a system failure (Roberts, Hughson, Smith, McIlveen, & Murray, 2006) which results in a degradation or outage of service. Infrastructure asset managers are charged with ensuring the proper functioning of these systems, but are faced with the task of managing and maintaining aging systems. The degradation of built infrastructures decreases their ability to reliably serve the public and so professional organizations and governments have highlighted the need for more emphasis on these systems. For example, the American Society of Civil Engineers regularly publicizes the degraded state of the United States infrastructure system (Powell, 2010) and the U.S. government has been working since the early 1990s to protect these infrastructures at the national level (President's Commission on Critical Infrastructure Protection, 1996).

One method to understand infrastructure is through the characterization of these systems as networks. In networks, related system components are represented as nodes and the relationships between them as edges. Nodes produce, consume, or pass along resources to other nodes while edges are the pathways that these resources take to and

[3] The contents of this chapter will be independently submitted for publication by Valencia, Colombi, Sitzabee, and Thal to the *Journal of Management in Engineering*.

from nodes. As modern infrastructures have become more interlinked in recent decades, understanding an infrastructure's network properties has become more important as we realize our understanding of cascading effects from infrastructure disruptions is not well understood (Zimmerman & Restrepo, 2009).

The National Research Council (2005) reported that the study of networks as a science and its applications to technological and social systems is still, however, in its nascent stages. Some early applications of network science to built infrastructures can be found in the literature. For example, some researchers explore the meaning of topological network properties such as degree connectedness, clustering coefficients, and characteristic path length for use in risk and vulnerability analysis (e.g., Dueñas-Osorio, Craig, Goodno, & Bostrom, 2007; Lewis, 2006) whereas others demonstrate the application of network science to existing infrastructures (e.g., Al Mannai, 2008; Dueñas-Osorio, Craig, & Goodno, 2007; Dueñas-Osorio, Craig, Goodno, & Bostrom, 2007; Nozick, Turnquist, Jones, Davis, & Lawton, 2004). These papers focus primarily on the application of network techniques to the protection of critical infrastructure systems from vulnerabilities such as terrorist attacks and natural disasters.

One source of vulnerability to infrastructure systems is decay through aging, but studies into the issues of infrastructure aging are not well represented in the literature. Some initial work has begun, one example being the Aging Infrastructure Workshop sponsored by the Department of Homeland Security (Doyle & Betti, 2010). The workshop acknowledged the role that decay contributes towards increasing risk to infrastructure systems. Topics of the workshop varied widely from the general, present conditions of the nation's infrastructure, to broad ideas such as the economic and social impacts of infrastructure failure, to more technical domains such as structural health monitoring and decision-making methodologies. This collection of works illustrates the need to better understand infrastructure aging.

This chapter strives to further the research of infrastructure systems as networked systems as well as provide a method which addresses infrastructure aging. It proposes to provide insight into interdependency analysis of infrastructure distribution systems at a municipality level. The organization of the chapter is as follows. First, a brief discussion on networks as applicable to infrastructure systems is presented. The degree sequence distribution, which is a key descriptor of network structure, and infrastructure interdependencies are discussed as these two concepts lead to a method in identifying critical network components. Next, a method is proposed which is a modification of the input-output inoperability model (IIM). The IIM has primarily been used to study economic interdependencies, but the modified method proposes that physical and geographic interdependencies can be modeled and understood to provide insight into the effects of aging components on an infrastructure system. Finally, the data acquired is briefly described and the paper closes by applying the method and discussing the results of the work.

4.2 Network Analysis in Infrastructure

4.2.1 Network Structure.

There are generally four classes of networks: regular networks, small-world networks, scale-free networks, and random networks (Lewis, 2009). Each of these network classes have their own unique properties. Regular networks have zero randomness in their structure, so the number of connections and the pattern of these connections is the same and predictable for all nodes across the system. Random networks have no discernible structure as the connections between nodes are completely random. Scale-free networks are characterized by having a small number of nodes with a high number of links, and small world networks are characterized by the existence of node "neighborhoods" that are connected through intermediary nodes.

In describing the network connections for nodes across all four classes of networks, the degree sequence distribution provides some interesting properties for the different classes of networks. Based on the node degree, which is a count of the connections for any given node, the degree sequence distribution is a histogram that plots the percentage of nodes with a particular degree against a list of all the degrees in the system. In a regular network, the degree sequence distribution is a uniform distribution of 100% for a single degree since the number of connections of every node will be that degree. In a random network, this distribution follows the binomial distribution since the number of connections for any given node is completely random. For small-world networks, the degree sequence distribution is similar to that of a binomial distribution, but with a taller and thinner shape for the histogram plot. Finally, in scale-free networks, the degree sequence distribution follows a power law distribution which indicates the existence of network "hubs" where a small fraction of nodes have a high number of connections.

For built infrastructures, scale-free and small-world networks are commonly used to describe the structure of these systems. Lewis (2006) finds that critical infrastructure systems such as the internet, railroads, interstate transportation, and gas and oil pipelines have structures that classify them as scale-free networks. Within these networks are a handful of hubs which are connected to an overwhelmingly large share of nodes compared to the average node. Within the interstate transportation network, for example, Lewis (2006) suggests that major cities represent hubs as they have many more interstate connections relative to smaller sized cities and towns. For small-world networks, Lewis (2006) finds that the national power grid forms clusters of nodes (neighborhoods) and thus can be classified as a small-world network. By identifying the structure of the network, it is then possible to identify critical hubs or critical node clusters which could form the basis for management and maintenance policies for built infrastructure systems.

4.2.2 Infrastructure Interdependencies.

Along with network structure, another important concept in understanding infrastructure networks is the characterization of network interdependencies. Work by Rinaldi, Peerenboom, and Kelly (2001) has facilitated research in infrastructure networks by providing the basic definitions of infrastructure interdependencies. To begin, interdependencies differ from dependencies based on whether or not the relationship between two entities is reciprocal. That is, an infrastructure *dependency* between two systems exists if flow from one system to the next occurs in a single direction. Outputs from System A are inputs to System B and B does not reciprocate to A. System B is dependent on System A and flow occurs in a single direction from A to B. An infrastructure *interdependency*, on the other hand, is bi-directional for these two systems where the infrastructure outputs are mutually relied upon by the infrastructure systems, or elements of the systems. Although conceptually simple, the idea of interdependencies increases system complexity as behaviors are created which are not intuitively predictable.

Furthering their definition of interdependency, Rinalidi at al. (2001) establish four classes of interdependencies. *Physical interdependencies* are relationships based on the material outputs from one infrastructure being passed to another as a material input. These infrastructures pass physical products that are used as resources to each other. For example, an electrical generation plant provides electricity to a water station pump house which reciprocates by delivering water to the plant for cooling. Degradation of one system affects the flow of physical objects in the interdependent relationship, thereby affecting both systems.

Cyber interdependencies exist when information is the entity being passed between infrastructures. Modern infrastructures are heavily reliant on information technology for their operation and monitoring. Supervisory control and data acquisition (SCADA) systems that allow for the remote control and monitoring of industrial and infrastructure processes are examples of cyber interdependencies. To affect systems with a cyber interdependency, one would have to influence the flow of information for these systems.

Geographic interdependencies are based on physical proximity. These systems are spatially situated such that a localized event affects the status of these infrastructures. Severe weather, explosions, and accidents are examples of events that might affect the status of geographically interdependent systems. The physical effects of the event might manifest itself as damage to system components within the same geographic area and result in disruption in service for the infrastructures affected.

Logical interdependencies exist between infrastructures when there is a reciprocal relationship that is (1) neither physical, cyber, nor geographical and (2) is described through logical reasoning. For example, if "government" is described as an infrastructure system, this system creates policies and plans in the management and operation of physical infrastructure systems. Reductions in maintenance and repair budgets would degrade the service delivery of these systems, yet "government" relies on these systems in order to continue operations. Government does not provide physical resources to other systems, meaning there is no physical interdependency; nor does it provide data as a resource, meaning there is no cyber interdependency; and finally it may not be near other systems, meaning there is no geographical interdependency. It does nonetheless impact the operation and delivery of infrastructure systems under its authority and through reasoning, a logical interdependency between government and other infrastructure is defined.

This interdependency framework provides the basis for modeling and simulation methods that might link different infrastructure systems. Whether it is a physical infrastructure, such as a water distribution system or road network, or an abstracted, "soft" infrastructure, such as a healthcare system or economic infrastructure, one of the four interdependency types will describe the interconnection between two or more systems. Combined with the understanding of the network structure of scale-free or small-world for infrastructure systems, methods can be developed that identify the critical nodes in a system of multiple, interconnected networks.

Finding such methods is particularly salient for infrastructure systems as these systems are nearing, or have surpassed, their expected useful life. One particular challenge is the limited resources available for the operations and maintenance of the systems. Infrastructure systems are large and geographically expansive with many components. Rarely is it the case that all necessary resources are provided to ensure the infrastructures are in perfect working order. Rather, some deterioration is accepted by both infrastructure managers and the general public with repair prioritization being the general philosophy. Understanding interdependency effects within a system of infrastructure systems will aid in identifying the most important components towards developing a prioritized maintenance and repair policy, as well as policies regarding the mitigation of cascading failures resulting from network interdependencies.

4.3 IIM Overview

The method that we propose to understand interdependency effects is a modification of the input-output inoperability method (IIM) (Haimes & Jiang, 2001; Haimes, 2009). Based on the Leontief input-output economic model of interdependencies, the IIM captures the spread of the "risk of inoperability" in a networked system through matrix algebra operations. One key to the model is the introduction of node inoperabilities. The idea of inoperability is likened to reliability – a particular network component is assigned a percentage that illustrates its probability of failure – but unlike reliability, inoperability also describes node interdependency. In Figure 12, Nodes A and B are dependent on each other (i.e., interdependent). If Node A were to fail, Node B would lose 40% of its operating capacity; and if Node B were to fail, Node A would lose 60% of its operating capacity. For this example, the IIM would assign the edge from A to B a weight of 0.4 and the edge from B to A a weight of 0.6.

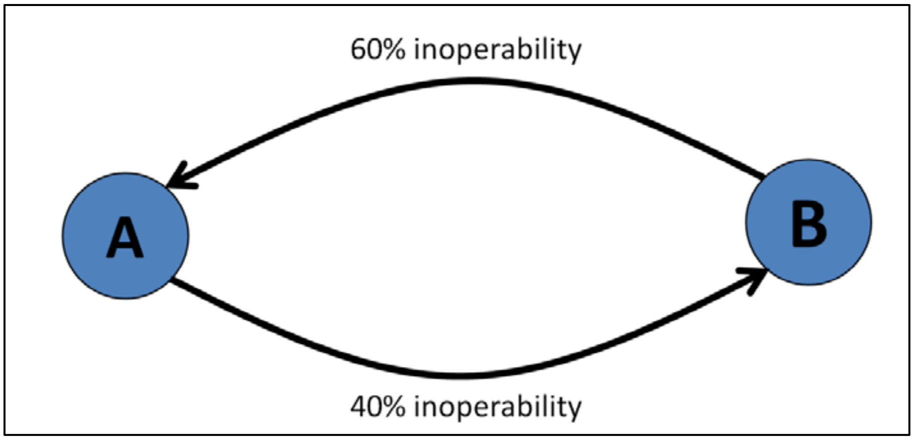

Figure 12. Interdependency for a two-node network.

In any system, the connections between nodes can be captured in a weighted adjacency matrix. Such a matrix would be a square matrix with the column and row indices being the node labels and each entry being the weight of the adjacency. For the example in Figure 12, the adjacency matrix would be a 2 x 2 matrix with a total of four entries. Adjacency matrices can be scaled up as any network topology can be captured in this simple, two dimensional construct. By mathematically capturing the network topology in matrix form, the IIM can model the effects of node interdependencies through basic matrix operations.

To understand the effect of a perturbation in a network, two additional components to the model are needed. First, an input to the system is required which models a network disturbance. In the IIM, this disturbance is illustrated through a column vector, called the scenario vector, whose entries are a list of the network nodes. An entry greater than zero indicates some level of inoperation (i.e., failure) for that particular node. For example, an entry of 0.5 would indicate 50% inoperation of a particular node (or 50% operability) while an entry of 1.0 would indicate 100%

inoperation (or complete failure of that node). Second, the output for the system, called the damage vector, which is also a column vector, lists the results for each network node. Interpreted in the same manner as the scenario vector, the damage vector is the resulting inoperabilities from application of the scenario vector. In compact matrix form, the IIM model is,

$$\mathbf{q} = \mathbf{A} \cdot \mathbf{q} + \mathbf{c} \tag{4.1}$$

where **A** represents the interdependency **A**-matrix, **c** is the scenario vector, and **q** is the resulting damage vector. The size of each component in the model is driven by the number of nodes in the network. Therefore, an *n*-sized network would result in an *n x n* square matrix for the interdependency **A**-matrix and n x 1 column vectors for the scenario and damage vectors. Solving Equation 4.1 is simply,

$$\mathbf{q} = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c} \tag{4.2}$$

where **I** is the *n x n* identity matrix.

Since the **A**-matrix captures network topology for any network, the IIM can be used to study any of the four infrastructure interdependency types outlined by Rinaldi et al. (2001). However, much of the work to date that utilizes the IIM has been in the study of economic interdependencies between large sectors of a given economy. In fact, Haimes (2009) describes that the adaptation of the IIM from Leonteif's I-O model is advantageous due to the availability of infrastructure interdependency data through two major databases: the Bureau of Economic Analysis (BEA) and the Regional Input-Output Multiplier System (RIMS-II). These two databases provide detailed information on the production and consumption of resources among differing economic sectors and are used as the basis for the interdependency **A**-matrices. Therefore, the IIM has been primarily used in the understanding of mostly economic relationships among large industrial sectors.

4.4 Proposed Modification to the IIM

This study departs from the customary application of the IIM to economic interdependencies and instead analyzes physical interdependencies of smaller, localized networks. Rather than modeling an entire infrastructure sector as a single node, this study proposes that the IIM can be used to understand interdependency effects within municipal level networks. To do so, however, we propose several major modifications to the IIM model.

First, the scale of the infrastructure networks is small and the level of detail is greater in the proposed model, compared to that of an entire economy in the IIM. Rather than abstracting economic sectors as a node, which themselves could be networks, we propose that each node now represents a component of a municipal infrastructure. The level of analysis that can be achieved will be driven by the level of detail available. For this study, the use of geospatial information system (GIS) data provides information on facility level assets such as buildings, water towers, and substations. This smaller scale and higher level of detail is beneficial as it accounts for individual components of the system, thereby leading to strategies in the management of these components.

Second, the **A**-matrix developed for each infrastructure system is based on physical connections between components, with each connection considered binary. In most forms of the IIM, **A**-matrix entries are continuous values between 0 and 1. These entries are typically derived from the normalization of values from the economic databases which record inputs and outputs between economic sectors (Haimes, 2009). For the present study, we propose that the existence of a connection and its directionality is sufficient to analyze physical infrastructure interdependencies. Therefore, entries in the **A**-matrix are either 0 or 1, with 0 indicating no connection and 1 indicating a physical connection. In addition, the directionality between nodes is captured such that a 1 indicates a positive flow from a source node to a receiving node and 0 for the reverse. In this form, the **A**-matrix is simply the transverse of a directional adjacency matrix.

Third, we propose that utility lines be modeled as nodes within the system rather than as edges. Under this construct, utility lines are viewed as components of the system whose primary purpose is the transfer of resources to other nodes. Again, the existence of a connection would represent an edge between two or more nodes. Modeling utility lines in this way has two primary advantages. First, this allows the IIM to capture their role within an interdependent network. Considering utility lines as edges excludes them from IIM analysis as they are excluded from the adjacency matrix. Their existence is implied through the connection of two nodes in this form of an adjacency matrix. If a utility line is modeled as a node, however, the resulting adjacency matrix explicitly accounts for their physical existence while still recording the resource inputs and outputs for the line. The second advantage is that this method will account for utility line attributes such as failure rates, age, and interdependent effects just the same as other components in a utility system. Utility lines are a critical component of any built infrastructure system and this third modification to the IIM allows for the capturing of their interdependency effects in a networked system.

With these three modifications proposed, two significant new ideas can be introduced. First, when dealing with a single system, a new network metric based on the count of nodes affected by a single node outage provides a measure of system dependency for every node in the system. The calculation of the IIM for the inoperability of a single node results in a **q**-vector that indicates the resulting states for each node in the system. Using Equation 4.2, we modify the model to produce results for each node, *i*, in the system:

$$\mathbf{q}_i = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c}_i \tag{4.3}$$

such that,

$$\mathbf{c}_i = \begin{bmatrix} c_{i,1} \\ \vdots \\ c_{i,j} \\ \vdots \\ c_{i,n} \end{bmatrix} \qquad c_{i,j} = \begin{cases} 1, & j = i \\ 0, & j \neq i \end{cases} \tag{4.4}$$

In Equations 4.3 and 4.4, the subcript *i* denotes the analyzed node. Therefore, $\mathbf{c}_i$ represents a vector that assigns an inoperable state for node *i*, while the remaining nodes in the system are considered fully operable. Vector $\mathbf{q}_i$ is the result of applying vector $\mathbf{c}_i$. The elements in the resulting $\mathbf{q}_i$ vector will either be zero, which indicates no effect from the inoperable node, or greater than zero, which indicates that there is some effect on that particular node. The number of resulting $\mathbf{q}_i$ vectors is equal to the number of nodes in the system. Thus, the results from inoperation of each node in the system can be analyzed.

To measure the level of dependency for a given node, a count of the affected nodes in each calculation is derived from each $\mathbf{q}_i$-vector result. Any element with a value greater than zero is added to this count and the summation is calculated as,

$$dep\_score(i) = \sum_{j=1}^{n} \mathbf{q}_{i,j} \qquad \forall i, j \tag{4.5}$$

where $\mathbf{q}_{i,j}$ is an element of the vector $\mathbf{q}_i$ and the interdependency score, *dep_score*(*i*), is a function of the node *i* whose inoperability is assigned 1. This dependency score provides a metric for the number of nodes affected in the network and provides a means for evaluating the importance of a node relative to another node through the identification of the physical interdependency levels of each node.

The second significant idea proposed is the ability to identify geographic interdependencies strictly from the results of the interdependency score. Owing to the use of GIS data, the location of the most critical system components can be visually depicted through the normalization of the physical interdependencies determined from Equation 4.5. Therefore, we propose a second metric called the geographic interdependency score to be:

$$geo\_score(i) = \frac{dep\_score(i)}{\max[dep\_score]} \qquad \forall i \tag{4.6}$$

where max[*dep_score*] is the maximum of all dependency scores for all nodes in the system. Through normalization, the resulting values can be used to render the vector data of each component in a GIS system. The results of this process highlight the differing levels of physical interdependencies and provide a visual method for identifying geographic interdependencies.

To address the impact of aging infrastructure systems, Monte Carlo simulation can be used with the IIM to simulate the inoperation of each node in the system according to some pre-determined distribution function. Given that each $\mathbf{c}_i$ vector only has one inoperable node, applying a distribution function to the vector is simply a matter of applying a distribution function to the node of interest, $c_{i,j}$, as in Equation 4.7.

$$\mathbf{c}_i(t) = \begin{bmatrix} c_{i,1} \\ \vdots \\ c_{i,j} \\ \vdots \\ c_{i,n} \end{bmatrix} \qquad c_{i,j} = \begin{cases} F_j(t),\ j = i \\ 0,\ j \neq i \end{cases} \qquad \forall i,\ j \tag{4.7}$$

where $F_j(t)$ represents the cumulative distribution function unique to node *j* and is a function of time, *t*. The distribution function should be representative of the expected failure rates for a particular component over time. Once distribution functions are determined for each node, the Monte Carlo simulation method can be used to first estimate the value of the function at time, *t*, for node *j* and then calculate each dependency score through an iterative IIM calculation for each time, *t*, as in Equation 4.8:

$$\mathbf{q}_i(t) = [\mathbf{I} - \mathbf{A}]^{-1} \cdot \mathbf{c}_i(t) \tag{4.8}$$

For every node, *i*, and every time, *t*, the model produces a dependency score which can then be plotted. Such plots show the effect of network dependencies and how these change over some period of time. Through this modification of the IIM, we are able to provide a dependency analysis of any infrastructure network as a function of time, the physical interdependencies of the system, and the particular node of interest.

One final modification to the IIM can be implemented which provides an understanding of system interdependencies. Up to this point, the IIM has been applied to nodes within the same system. As flow for these distribution systems has been from source to sink nodes and hence one-way, the relationships between nodes has been, by definition, dependency relationships. There are, however, dependency relationships that cross infrastructure systems and which form the bi-directional relationships necessary for interdependencies. To measure these interdependencies, we propose the introduction of mapping layers to the IIM.

A mapping layer captures those nodes that participate in multiple systems and thus propagates an inoperability from one system to the next. For example, a component such as a fuel pumping station participates in both the electrical infrastructure, as it requires electricity to operate, and the fuels infrastructure, so as to pump fuel. If an outage were to occur in the electrical infrastructure, a dependency analysis would reveal all the nodes that are affected within the electrical layer. This of course would identify the pump station and a second analysis on the fuels infrastructure would be required to identify the effects within the fuels layer. A mapping layer would integrate these two infrastructures by identifying that the pumping station operates in both layers and transfers an inoperability from one layer to the next, as shown in Figure 13.

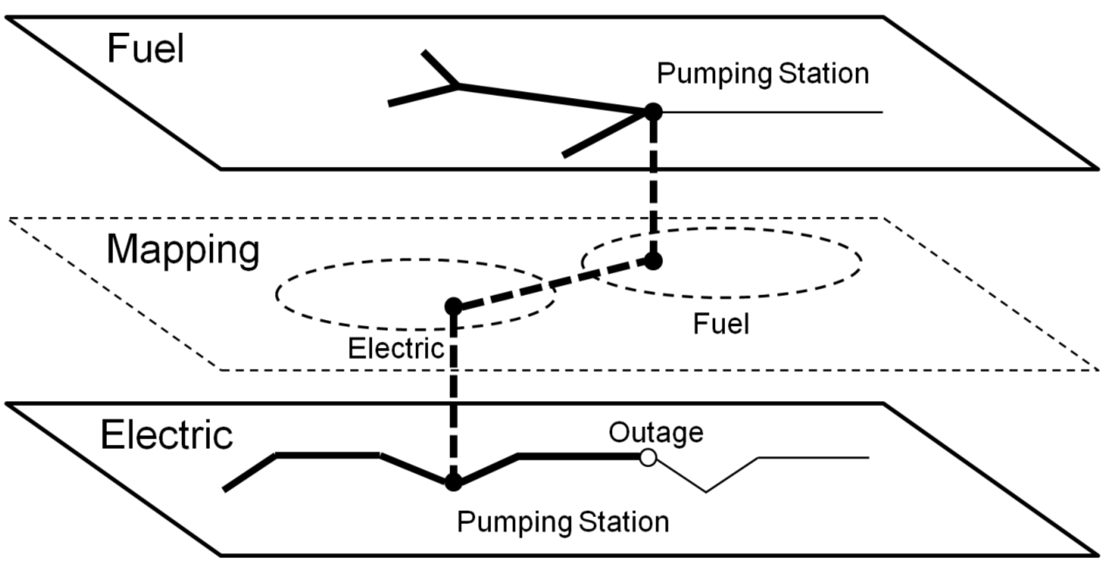

Figure 13. A mapping layer transfers inoperabilities.

To incorporate this mapping layer into the proposed modifications, the mapping layer is simply a directional adjacency matrix of nodes between two interacting layers. The node list of one layer would compose the matrix row indices while the node list of the second layer would compose the matrix column indices. For the scenario described in Figure 13, the electrical layer transfers inoperabilities to the fuels layer; therefore, the electrical node list would compose the row indices while the fuels node list would compose the column indices. This follows typical matrix convention where the "from" nodes comprise the row indices and the "to" nodes make-up the column indices.

To employ this mapping layer, an interim calculation is necessary which transfers the inoperabilities from one layer to the next. Therefore, the calculations necessary to carry out the interdependency analysis take on an iterative procedure using Equations 4.9 through 4.12,

$$\mathbf{q}(i)^{m} = [\mathbf{I} - \mathbf{A}^{m}]^{-1} \cdot \mathbf{c}(i)^{m} \tag{4.9}$$

$$\mathbf{c}(i)^{m \to m+1} = \mathbf{I}^{m \to m+1} \cdot \mathbf{q}(i)^{m} \tag{4.10}$$

$$\mathbf{q}(i)^{m+1} = [\mathbf{I} - \mathbf{A}^{m+1}]^{-1} \cdot \mathbf{c}(i)^{m \to m+1} \tag{4.11}$$

$$\vdots$$

$$\mathbf{q}(i)^{n} = [\mathbf{I} - \mathbf{A}^{n}]^{-1} \cdot \mathbf{c}(i)^{n-1 \to n} \tag{4.12}$$

where the superscript $m \to m+1$ denotes the mapping of an inoperability from one layer, m, to the next layer in the sequence, $m+1$. The vector $\mathbf{c}(i)^{m \to m+1}$ is the scenario vector which captures the transfer of the inoperability from layer m to layer $m+1$ and is used to calculate the $\mathbf{q}(i)^{m+1}$ damage vector. Alternating between Equations 4.10 and 4.11 is carried out until all layers have been exhausted.

At the conclusion of the calculation for a single node *i*, what remains are *n* damage vectors, $\mathbf{q}(i)$, for each layer 1, *m*, *m+1*, …, *n*, resulting from the outage of this single node, *i*. Collecting the results from these damage vectors, and only the maximum result for any node appearing in multiple damage vectors, provides a final damage vector result from the interdependency inoperability analysis of a single node. Repeating the above procedure for each node, *i*, in the system provides a complete interdependency, system-wide analysis. Similar to Equation 4.5, the summation of the collected values provides a measure of the level of interdependency for each node; this value can then be used to determine the relative importance of nodes throughout the entire infrastructure system.

Through several modifications of the IIM, this study proposes that physical dependencies can be used to identify geographic interdependencies as well as inter-layer system interdependencies. The three modifications proposed include studying smaller, more localized networks rather than large infrastructure sectors, capturing the physical connections between components to comprise the **A**-matrix, and characterizing utility lines as nodes in the system. These ideas together lead to two new metrics, the dependency score and geographic interdependency score, which provide the level of dependency or interdependency a system has for any single node. These metrics can help identify the most critical system components, as well as geographic areas, that might contribute to cascading effects of system failure. The next section discusses the application of the proposed method to geographic data obtained for a system of four infrastructures.

4.5 Method Application and Results

Figure 14 presents a portion of the geographic data obtained on four utility systems that provide electricity, heating and cooling, and water for a small municipality. In addition, data was also available for the liquid fuel system that services the aerodrome for the municipality. The area under current study is approximately 16.5 square miles in size and contains nearly 1,700 facilities serviced by the four selected infrastructure systems. These facilities range from multi-story office complexes to small latrines at outdoor recreation fields.

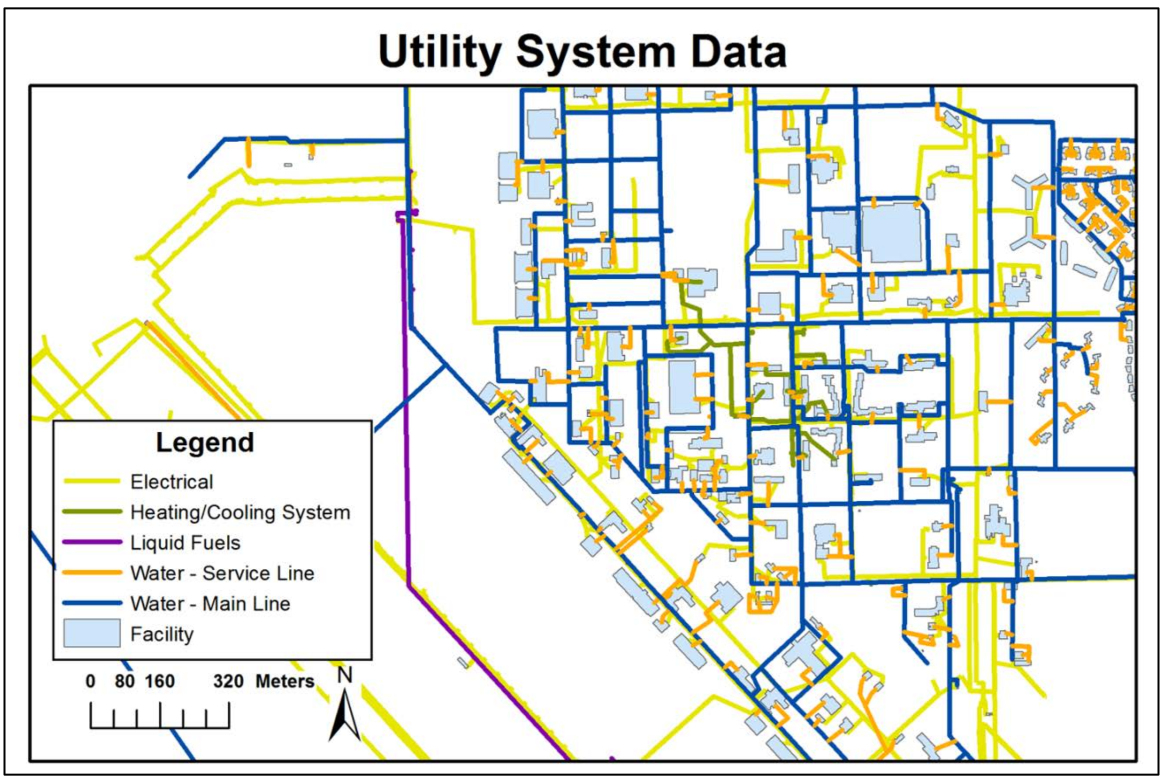

Figure 14. Portion of GIS data with four infrastructure systems and facilities.

ArcGIS 10.0, a common GIS platform developed and distributed by the Environmental Systems Research Institute, was the software platform used in the storage and display of the geospatial data obtained. In addition, Python, an open-source, object oriented programming language, was utilized in extracting the network topology for each system as well as executing the modified IIM model. This programming language is well supported within ArcGIS 10.0 and served as a useful tool in the topological cleaning needed to prepare the data. Extensive editing was necessary as the majority of utility line endpoints did not coincide with other line endpoints or points to a facility. The data in its original state did not model any sort of network topology, thus precluding it from network analysis. Using Python, a series of scripts were written which edited the data to correct topology errors, build well-formed and connected graphs, extract the resulting topological information, and finally run the proposed IIM model. Appendix C provides details on some of the topological corrections that were made.

After data preparation, the GIS data represented networks of physically interdependent nodes. The network sizes varied with the heating/cooling system and fuels distribution being rather small, while the water and electrical distribution systems were significantly larger. Table 1 presents several metrics that are commonly used to characterize networks (Lewis, 2009).

Table 1. Network metrics of utility systems under study.

System	*Size (Nodes)*	*Network diameter*	*Average degree connectedness*	*Cluster coefficient*	*Density*
Heating/cooling	33	9	1.94	0.0	.032
Fuels distribution	56	16	1.96	0.0	.019
Electrical system	2,788	39	2.07	0.011	.00072
Water distribution	4,331	74	1.87	0.003	.00028

Table 1 provides several basic facts about the structure of the networks. First, the magnitude of the size differences between the two small networks (heating/cooling and fuels) and the two large networks (water and electrical) is quite dramatic. The differences in the network sizes are measured in the metrics of size and network diameter. Size is a count of nodes in the network and network diameter is the length of the longest path in the system. Comparing the values of these two metrics reveals that the two smaller networks simply service far fewer facilities and are comprised of far fewer components than the two larger networks. Examining the differences between the water and the electrical networks reveals that there are significant differences in the modeling of the utility lines within the GIS data. The water layer contains more utility line segments than the electrical layer. Whereas the electrical layer may use a single line to represent a portion of its distribution system, the water layer may use three, four, or five segments to represent the same equivalent length of line. The water distribution system models more components to its network, thus the larger network size, but the two systems service the same facilities and occupy the same general geographic area.

Second, the measures of average degree connectedness, cluster coefficient, and, to some extent, density suggest an underlying tree structure for the four networks. Degree connectedness, a measure of the number of edges connected to each node for each of the networks, averages approximately 2.0. Given that each network is directional, each node in its respective network most likely has a single incoming edge and a single outgoing edge. This is not the case for sink and source nodes in the systems which have either a single incoming or single outgoing edge. Accounting for sink and source nodes explains why three of the four measures are slightly less than 2.0. The cluster coefficient measure provides additional evidence of the tree structure. Cluster coefficient is a measure of the likelihood of nodes clustering together through connections to each other. The coefficients in each of the networks are very low, with the first two being zero. A zero cluster coefficient indicates that there are no clusters formed, that is, nodes do not have common neighbors. The low coefficients for water and electricity indicate that some clustering occurs, but the vast majority of nodes do not form clusters. Finally, the low graph densities indicate extremely sparse graphs; this is in line with the density for a tree structured network. Given the average degree connectedness, the low clustering coefficients, and low graph densities, the underlying structure for each of the networks can be described as a tree.

With the tree structure, a problem arises in the identification of critical nodes when using common network topology measures such as degree centrality, degree closeness, betweeness, and degree sequence distribution. Each of these measures can be used to identify those nodes with the greatest connections within the network, concluding that they play a more important role (as "hubs") than less connected nodes. Indeed, examination of the degree sequence distribution can identify the most connected nodes as in Figure 15(a) for the water distribution system. The degree sequence distribution is skewed right with the highlighting of Water Line 2725 as a single node with a relatively high degree centrality of 16. Further examination of the identified line, however, reveals this water line only affects 16 service lines, Figure 15(b), which in turn affect 16 facilities. Using the common centrality measures would lead one to conclude that the identified line is the most important line in the system when, in fact, it plays a minor role in the operation of water distribution.

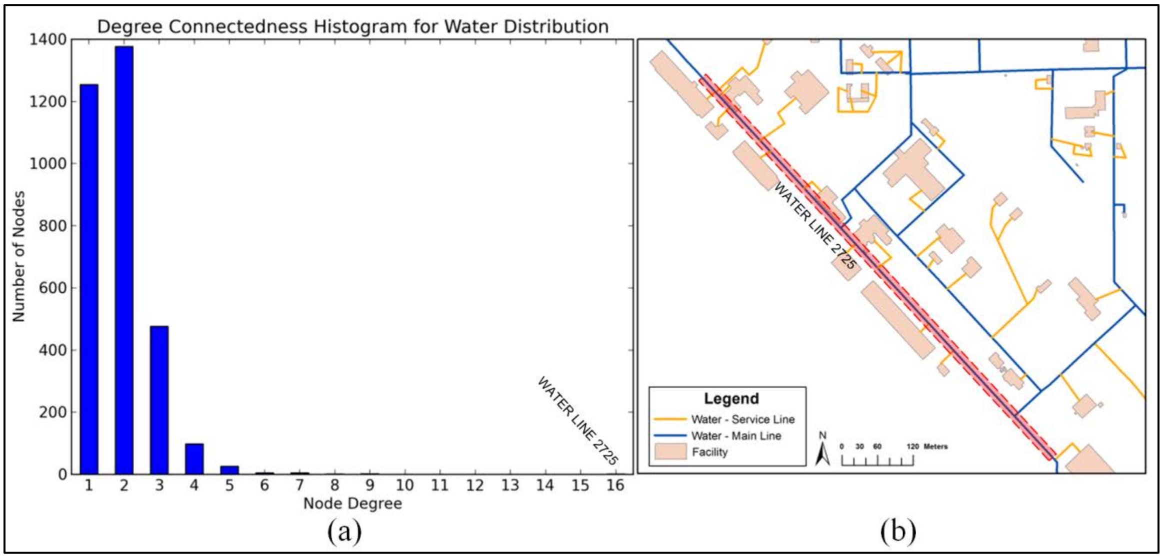

Figure 15. Analysis results using a common centrality measure.
(a) Degree connectedness histogram for water distribution.
(b) Examination of Water Line 2725 in GIS.

Applying the modified IIM reveals better identification of critical nodes in these infrastructure systems. Figure 16 provides plots of the modified IIM results for each of the four infrastructures systems. The horizontal axes represent individual nodes in the networked system with each axis ordered from greatest impact to least impact. For clarity, the labels for each system component in the figure are replaced with its ordering number. Therefore, Node 1 in each analysis will have the greatest impact among all nodes within its respective infrastructure system. The top two plots provide the results for all nodes in the system while the bottom two represent only the top third scoring nodes due to the sheer number of components. The vertical axes are the interdependency scores derived from Equation 4.5. These scores represent the total number of nodes affected by each node in the system. The greater the score, the greater the impact a particular node has within the system.

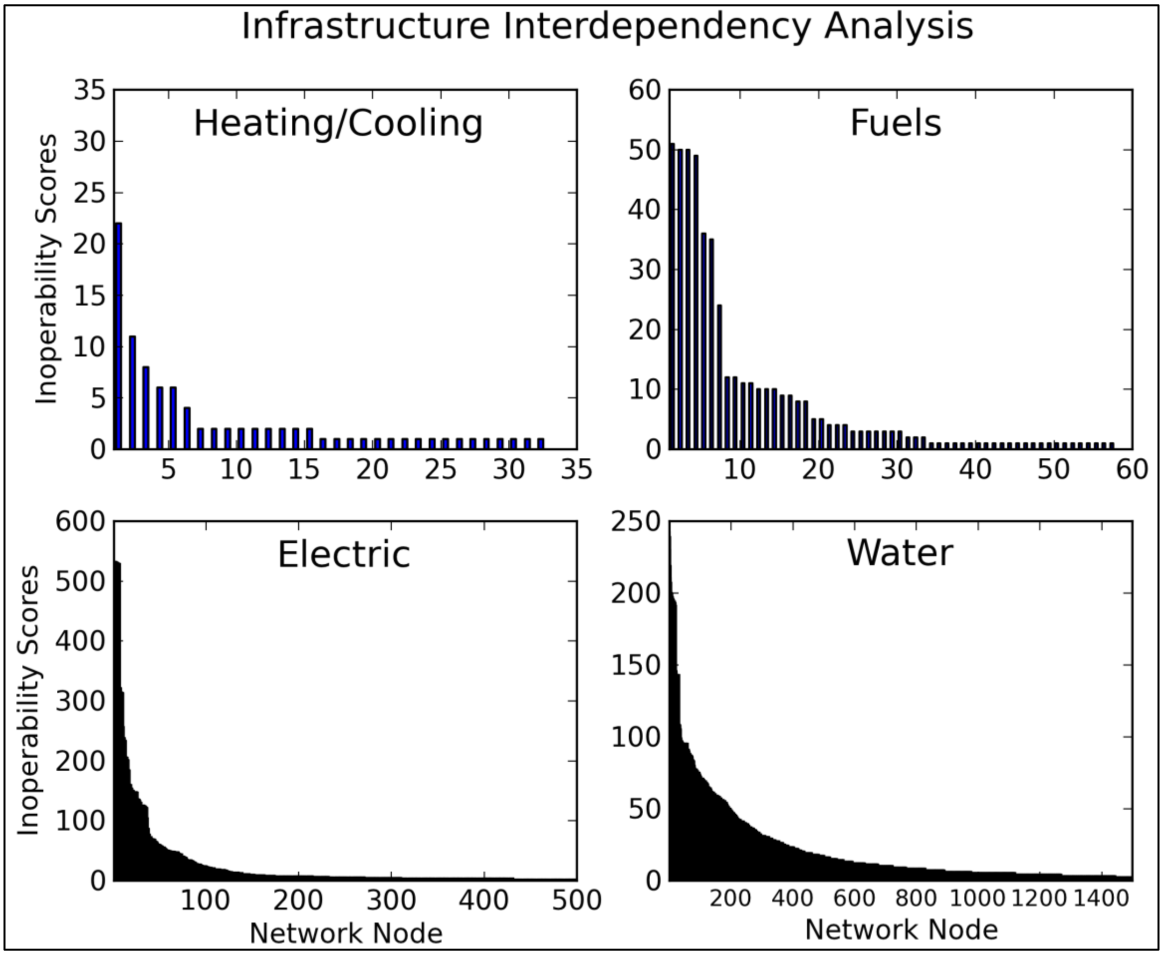

Figure 16. Interdependency analysis results.

The shape of the plots among all four systems is similar to that of Figure 15(a). This shows scale-free structure within the network and indicates the existence of network hubs (i.e., nodes with the highest degree connectedness within the network). The tree structure in all four of the infrastructure systems, however, leads to very few hubs which are in fact not at all critical. Instead, the modified IIM method properly identifies the source nodes, and immediately adjacent nodes, as the most critical nodes, since all resources flow through these nodes. An inoperability in these nodes affects the greatest number of nodes in the system. Therefore, the scale-free structure of the bar charts in Figure 16 indeed indicate the existence of hubs, but these hubs are a result of the indirect connections to other nodes in the network.

Using the results to identify geographic interdependencies leads to Figure 17. The figure was created by applying Equation 4.6 to normalize each dependency score and then applying a coloring scheme to identify the highest scoring nodes. The figure suggests that critical components for the fuels and electrical systems are geographically separated, while critical components for the water and heating/cooling systems display a geographic interdependency. Such an identified interdependency should lead analysts to explore the effects of one system on the other should failures, such as line breaks, in that area occur. One issue with the method of visual display of geospatial data is that larger sized components will receive more weight in their criticality than smaller components. That is, there are several high scoring facilities within the mapping area that cannot be seen due to their small geographic area relative to the area traversed by the utility lines.

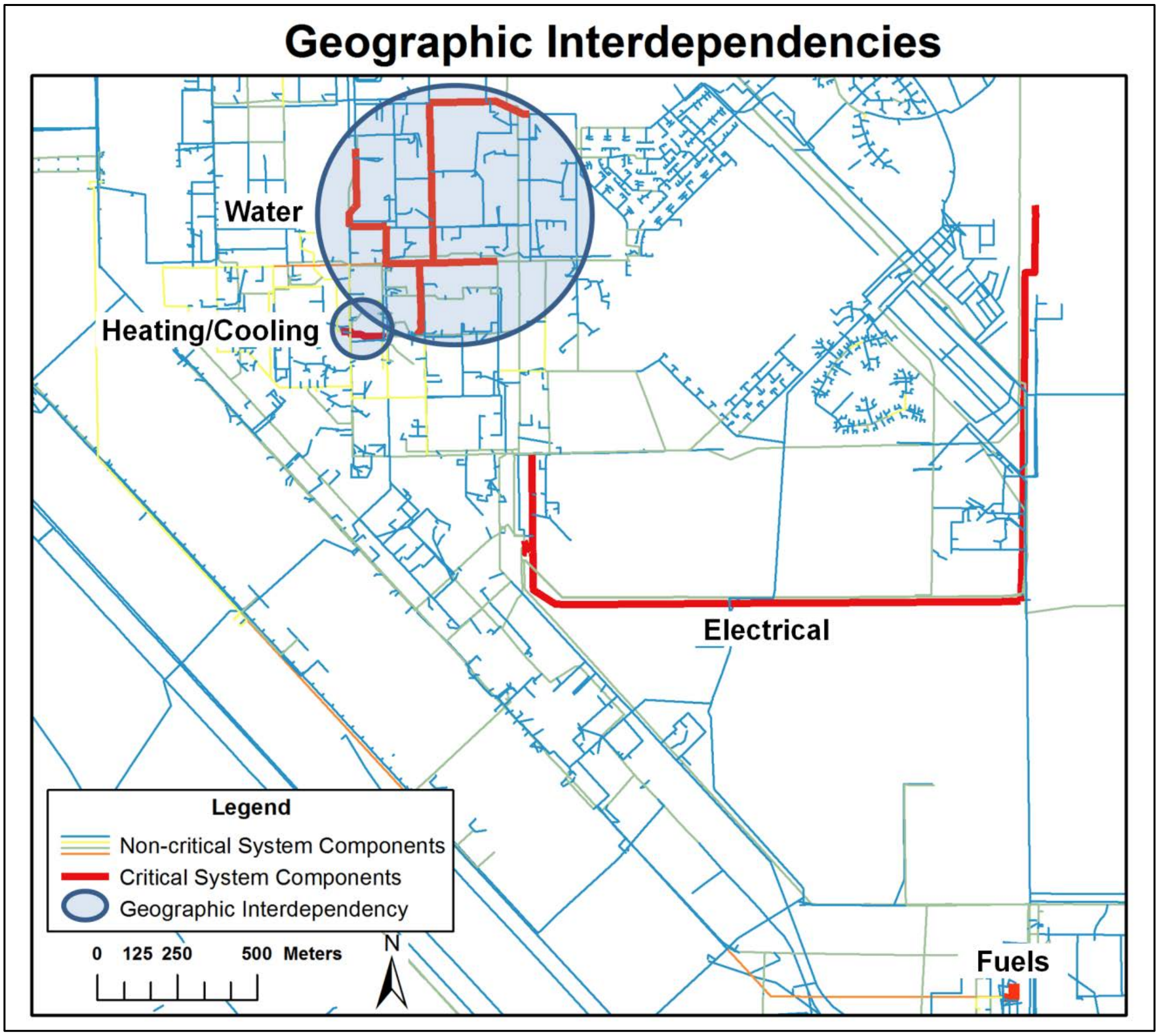

Figure 17. Identification of critical nodes and geographic interdependencies.

In another application, the method can be used to analyze the impact that interdependencies might have on aging assets. Using Equations 4.7 and 4.8, the impact of the failure for a particular node on a network can be plotted given a particular failure distribution. In the data collected, the build dates of various components and facilities of the system provided a starting point for the analysis since the age of each node provides an idea of the level of decay for that component. That is, the greater the age, the greater the likelihood of failure due to decay. Other data were required to be simulated, however. In particular, the cumulative distribution function for each component was assumed to be the Weibull distribution with a scale parameter of either 67 years for a facility or 100 years for a part of the distribution system. These values are generally accepted useful lifetimes for facilities and infrastructure systems (GAO, 2003; Hudson et al., 1997). Additionally, facilities and infrastructure managers accept that their systems are in a constant state of deterioration (*Stewardship of federal facilities*, 1998; Rush, 1991) and therefore aging can assume an increasing failure rate over time. Taking this into account, the Weibull shape parameter of 3.0 was subjectively chosen in the absence of data that might lead to any other specified value.

Given the establishment of decay distributions for every node, i, in the system, a Monte Carlo simulation approach can be applied in order to produce Figure 18. A sampling procedure of 1,000 trials for the Weibull distributions generates estimates of the inoperabilities for each node at each time, t. A time step of 0.1 years is established for the 40-year period and the estimated inoperabilities are used as entries into the $\mathbf{c}_i(t)$-vectors for every node. The resulting $\mathbf{q}_i(t)$-vector outputs are column summed, as in Equation 4.5, and plotted. This approach takes into account a network's topology along with component failure distributions to produce plots in order to show changes in node inoperability scores for each of four systems over a 40-year period.

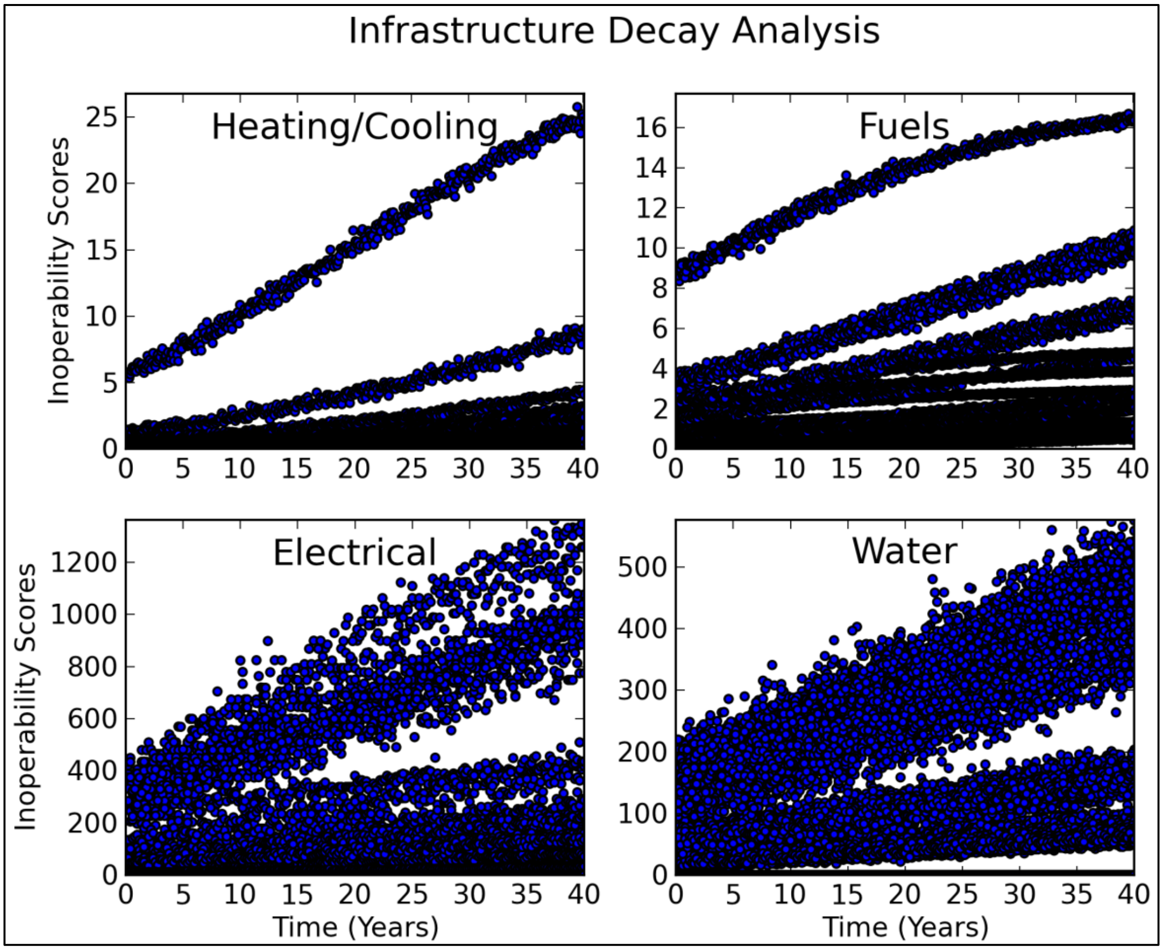

Figure 18. Results from Monte Carlo and the modified IIM simulation.

Figure 18 provides some insight into the changing interdependency effects as a function of time. Three of the four plots show a clear delineation of the most important nodes in the system and the predicted future impacts given the reliability functions for each node. The results for the water distribution system are not as clear due to the large number of nodes under analysis, but subsets of the water system could be isolated for more detailed study. Such results could be used in defining long-term management plans identifying critical components and the points in time in which they should be refurbished or replaced. Additionally, changing the scale of the study to a shorter term outlook would provide clarity on immediate likelihoods of failure and the impact on the overall system.

Finally, the inter-layer interdependency method introduced in Equations 4.9 through 4.12 returns a set of integrated results displayed in Figure 19. With this final output, the effects of the interdependencies of nodes across each of the four infrastructure systems is captured. Whereas Figure 16 shows that the maximum scores for the electrical and water system inoperabilities are approximately 600 and 250, respectively, Figure 19 shows that the maximum score for the most critical nodes in the inter-layer analysis are nearly 1,800. This is a significant departure from the results of any of the single layer analyses. The large increase is explained through the transfer of inoperabilities from system to system. The mapping layer mathematically integrates each of the disparate infrastructures and the analysis, therefore, treats all four networks as a single system.

Extracting the top scoring nodes in this analysis reveals that the most important nodes are the series of lines that feed into the municipality's electrical substation and the electrical substation itself. A natural break occurs in the data where the inoperability scores drop precipitously, thereby identifying nodes with a lesser inoperability impact. The nodes to the left of this break are classified as Group I and the nodes to the right are classified as Group II. The nodes in Group II are a mix of water infrastructure components and electrical components. Additional natural breaks can be found, and this risk analysis identifies three distinct groups of nodes. The inter-layer interdependency method is significant in that it relates all nodes within the four infrastructure systems equitably and provides a method for scoring their inoperability impact. This final method is useful as it equates disparate infrastructure systems and reveals those components with the greatest impact to their systems regardless of the infrastructure type.

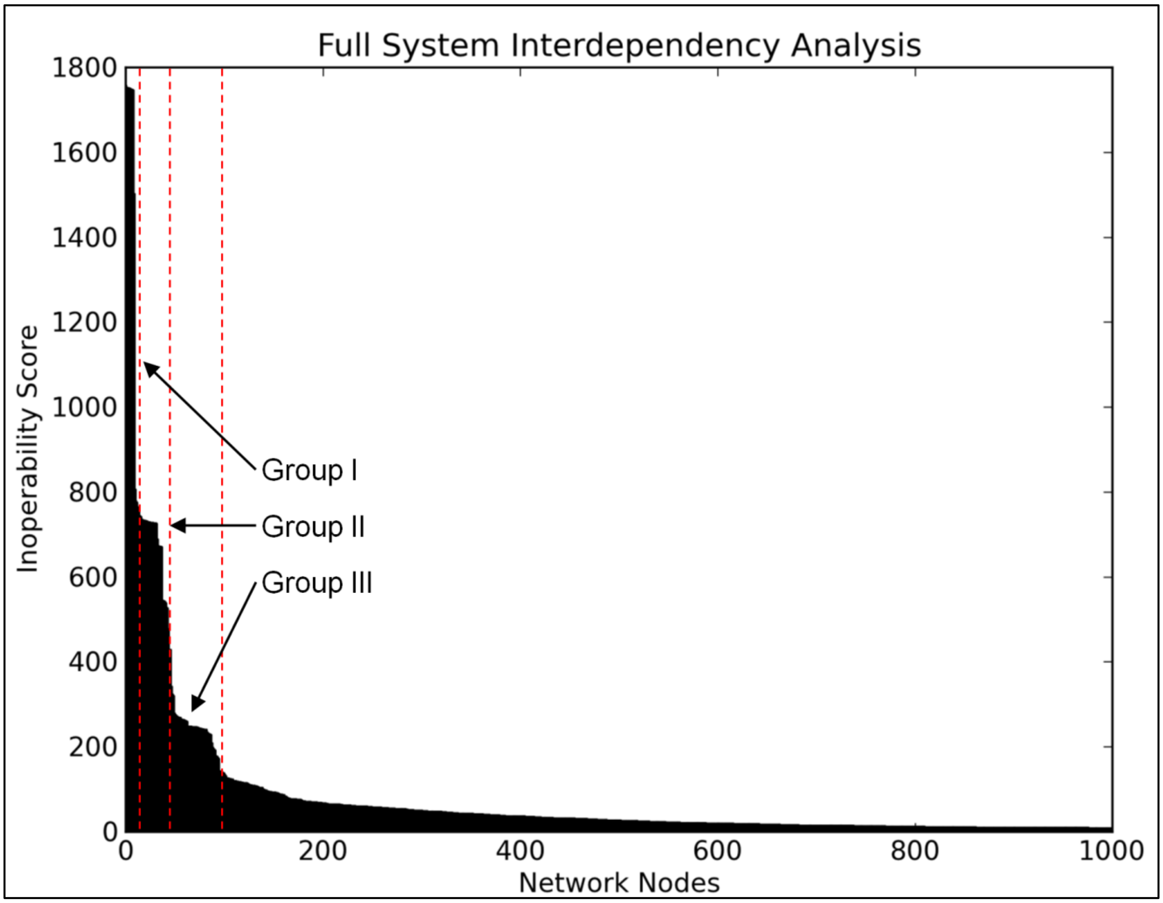

Figure 19. Full system interdependency analysis using the multi-layer IIM method.

4.6 Findings and Conclusion

The model presented in this work attempts to advance the state and understanding of network analysis techniques on built infrastructure systems by exploring physical and geographic interdependencies of a system of four infrastructures. These interdependencies were explored through several modifications of the IIM model. First, the model simplifies the interdependency **A**-matrix to Boolean entries only. Second, utility lines within the system are considered as nodes within the matrix, rather than edges; physical connections within the utility are then represented as edges. Third, a dependency score is utilized and quantifies the level of interdependency a particular node contributes to the system. Finally, this dependency score is the basis for geographic interdependency results and is central to a Monte Carlo simulation method which provides possible insight as to how interdependency effects might change over time.

Geospatial data on a system of four infrastructures were obtained for a small municipality and the results from the application of the method were presented. Several key findings are highlighted here as a result of the work.

- Simplification of the interdependency **A**-matrix facilitates the use of geospatial data alone to conduct an interdependency analysis.
- Modeling utility lines as nodes within a network provides a method which accounts for their role as interdependent components.
- The systems are found to be tree network structures and current network methods do not account for the importance of source nodes; the modified IIM identifies these source nodes as critical components.
- Importing model results back into a GIS platform provides a means to visually display results and aids in identifying geographic interdependencies.
- Applying Monte Carlo simulation to the modified IIM provides a means to project future maintenance requirements on aging systems, but asset management organizations must deliberately develop and maintain the necessary reliability data for their components.

There are several opportunities for future work regarding the modified IIM method. First, the model discounts the effect of facilities to a larger network and treats facilities as sink nodes where branches of the tree network end. An adaptation of the model which accounts for a facility's relative importance to a larger system will aid in the area of facilities management. Second, extensive topological cleaning was necessary to prepare the data for use in the model. As this dataset is representative of other geospatial data on utilities, development of algorithms that transform this data into topologically connected data will aid future network analysis methods on utility systems. Third, identification of geographic interdependencies in this work was limited to a visual analysis after importing model results back into a GIS platform. Applying known spatial analysis methods to these results might produce a quantitative means in identifying geographic interdependencies.

The proposed method presented herein provides a means to leverage existing geospatial data which identifies physical and geographic interdependencies within infrastructure systems. The method can also account for infrastructure decay effects on these networked systems. This paper models physical infrastructures as networked systems and strives to further the research in this area.

V. Conclusion

This final chapter is a summary of the research effort. It begins with a section that briefly addresses each of the research objectives posed as a question at the beginning of the study. Next, the significant findings and key contributions resulting from the work are discussed. Finally, recommendations for future work are provided.

5.1 Research Objectives

At the beginning of this research, the objectives to be addressed were developed such that the overall work had a focused area of study within infrastructure management. Infrastructure managers are coming to understand that decay is just as relevant a threat as extreme weather and purposeful attacks. In using network techniques to model built infrastructures, some insights have been gained, as well as a new model proposed, that might lead to better management of infrastructure systems. The research objectives leading to these conclusions were posed as questions in Section 1.4 and are briefly answered here.

- *How can risk to infrastructure be quantitatively modeled?*

  Modifications to the input-output inoperability model (IIM) were developed that allowed for its applicability to lower-level infrastructures (i.e., secondary distribution systems) where network topology was captured strictly with geographic information system (GIS) data. With this network topology, the modified IIM can be implemented to provide a measure for the criticality of a component to the overall system. The metrics introduced identify those components which are most critical to the system and, therefore, represent a greater source of risk than other components.

- *What aspects of networked systems (that is, what metrics) are applicable towards infrastructure risk analysis?*

  Conventional network metrics such as degree connectedness, cluster coefficient, and network density were found to have limited utility when applied to actual data on built infrastructures. Each system was found to have a tree network structure; therefore, these metrics offered little information in the way of critical components. The modified IIM created new metrics in identifying critical components.

- *How do interdependencies of networks affect this analysis?*

  Four types of infrastructure interdependencies are defined in the literature and this work explored analyzing two of these: physical and geographic. This study found that GIS data can facilitate the analysis of physical interdependencies, which leads to identifying geographic interdependencies. Several problems were identified in understanding interdependencies with the original IIM and these problems and their solutions are highlighted as a key contribution.

- *How can the concept of infrastructure decay be modeled and simulated so as to produce a valid infrastructure network risk model*?

  This research found that the principles of Monte Carlo simulation can be applied to the modified IIM to produce results that might predict impacts of decay from components onto the larger system. Additionally, this research suggests that modeling the utility lines as nodes in a network offers a more informed model as these lines also have decay properties. One issue discovered, however, is that infrastructure asset management organizations must maintain decay data at the individual component level to be able to understand infrastructure decay at the aggregated network level.

5.2 Significant Findings and Key Contributions

This section describes the significant findings and key contributions of the research. Although the focus of the study was very specific in its modeling and application, the outcomes might aid infrastructure asset managers as they develop and choose those policies which lead to better maintenance and management practices as their systems continue to age. Six findings and contributions are discussed here.

First, the simplification of the IIM model allows for the modeling of interdependencies and their effects in a networked system. Reducing elements of the interdependency matrix to Boolean values transforms the matrix to a directional adjacency matrix. This has the dual advantage of eliminating the reliance of IIM modeling on economic data, such as the Bureau of Economic Analysis data or the Regional Input-Output Multiplier System, and instead leverages the network topology contained within GIS systems. Additionally, the research found that GIS systems have the ability to solve network problems of a specific type: the shortest path problem. The modified IIM is a different type of network problem that GIS may be used to solve.

Second, the study reveals that secondary distribution systems represent tree network structures and that conventional network analysis methods do not account for the criticality of source nodes. One method, the degree sequence distribution, however, provided insight into finding critical components and was adapted into the modified IIM. In a network with hubs, the scale-free shape of the degree sequence distribution leads to identifying the most critical components. By building a similar histogram based on the results of the modified IIM, this same idea of hubs in a scale-free network provides a method in identifying "hubs" in a tree network. Although these hubs' physical connections were few, they have many indirect connections to other nodes in the network and, therefore, have the greatest impact on the system. These nodes are then identified as the most critical.

Third, the modeling of utility lines as nodes within a network, rather than as network edges, further informs the model by accounting for their role as interdependent components of the system. The modified IIM allows for this since the interdependency matrix captures a physical connection. Additionally, GIS data is already collected on each utility line allowing for the modeling of these lines as nodes.

Fourth, this research finds that applying Monte Carlo simulation to the proposed model provides a means for projecting future maintenance requirements on aging systems. Specifically, failure distributions assigned to each node in the system facilitates the calculation of the effect of that node over time. Applying Monte Carlo simulation leads to insights on changes to system risk over time. However, the research found that the infrastructure literature and asset management organizations suffer from a lack of data on the reliability of infrastructure components.

Fifth, a multi-layer model is proposed for analysis of multiple infrastructure systems as a single system. This research finds that a significant problem in understanding interdependencies with the original IIM was the model's limitation of representing an infrastructure network as a single, two-dimensional array. This had the problem of creating a very large and sparse matrix for a system composed of several infrastructures. To address this problem, the modified IIM leveraged the layered data structure of GIS systems to maintain the individual network systems. To integrate these systems together, the concept of a mapping layer was introduced which mapped components that appeared in differing infrastructures to one another. This mapping transferred inoperability effects from one layer to another and eliminated the need for a large, single matrix

Finally, the interdependent nature of infrastructure systems naturally introduces cycles and loops within the system. These cycles and loops create the problem of non-invertability of the model and this work presented a solution to the problem through the multi-layer framework. In maintaining the separation between infrastructure systems, an iterative calculation method was necessary to carry out the modified IIM. In addition to utilizing the mapping layer between infrastructure systems, the modified IIM was able to be calculated for all nodes and network layers and was able to account for interdependencies across multiple systems.

5.3 Recommendations for Future Research

There are several recommendations for future research as a result of the work contained in this study. Many of these recommendations were briefly provided in Chapters 2, 3, and 4 and are reintroduced and elaborated in this section. A total of five reccommendations for the direction of future work are offered.

First, the gap in data availability for infrastructrue component reliability is found to be a limitation in the study of infrastrucutre decay. To integrate Monte Carlo simulaton into the modified IIM, the reliabilities for each component in the system were estimated. Engineering data on component reliabilities were not available with the GIS data and, as such, the reliabilities were estimated in order to demonstrate the model's applicability with Monte Carlo simulation. Although development of component-level decay data for each component of an infrastructure system represents a significant challenge, understanding decay impacts of a networked system might be severely limited without such data.

Next, integrating the modified IIM model as an analysis module within GIS software platforms might be explored. As current methods available within GIS already solve shortest path problems, the possibility exists that GIS has the ability to solve a modified IIM as an integrated module. Doing so has the advantage of developing visual representation methods which display the IIM results. GIS systems are prevalent tools in the maintenance and management of infrastructure systems and integration of the IIM provides asset managers with a means for implementing the method.

The external effect of sink nodes in the system is another suggestion for future work. In the model, facilities are represented as sink nodes where the transfer of inoperabilities terminate. Since facilities do not transfer inoperabilities, the model discounts their role within the network as non-critical nodes. However, facilities play an important role external to the physical network and provide services or complete work necessary to the larger system. An adaptation of the model which accounts for a facility's importance to the larger system will aid in facilities management. Such adaptations might include exploring the two interdependencies not explored in this study: cyber and logical interdependencies.

Next, algorithms which address the lack of network topology within GIS data should be explored. Extensive topological cleaning was conducted to prepare the data for use in the model. The dataset acquired is representative of geospatial data maintained by other asset management organizations, so developing algorithms that transform this data into topologically connected data will aid in future network analysis methods.

Finally, exploring known spatial analysis techniques to results of the IIM model might better inform asset managers regarding geographic interdpendencies. In the current work, geographic interdependencies were identified visually after importing the model reults back into the GIS platform. Exploring spatial analysis on these results has two advantages. First, these techinques are readily available in common GIS platforms and, second, such techniques might produce a quantitative means to identify geographic interdpendencies.

Each of these research suggestions represent areas in the current work that would benefit from additional exploration. Along with these recommendations, the objectives of the research, and the key findings and contributions of the research were outlined. Together, the sections of this chapter summarized the overall research effort into the network analysis of built infrastructure systems.

Infrastructure systems have a significant impact on the world as they serve as the basic underpinnings of modern society. As current infrastructures age, there will be an increase on the emphasis for the proper management and maintenance for these systems. This research contributes towards that effort in its comprehensive network modeling of infrastructure risk and offers a sound method in understanding network interdependencies for built infrastructure systems.

Appendix A. Literature Review on Systems Engineering and Asset Management[4]

This appendix provides an overview of the literature in which an overlap between systems engineering and infrastructure asset management occur. It demonstrates that six systems engineering processes comprise the core processes of engineering asset management. The work provides a perspective on the necessity of taking a systems view in the practice of infrastructure asset management.

A.1 Introduction

In 1998, the American Society of Civil Engineers released its first "Report Card for America's Infrastructure" in which it awarded an overall grade of "D" for the national infrastructure. Since then, it has issued subsequent report cards in an attempt to highlight the impending failure of the nation's infrastructure and elevate infrastructure needs on the U.S. national agenda (Powell, 2010). However, infrastructure systems are complex, vast, and thus difficult to manage. Therefore, applying a systems approach to the management of civil infrastructure is gaining acceptance within the infrastructure asset management field (Godau, 1999; Hudson et al., 1997; Powell, 2010), but application of systems methods, processes, and techniques is limited and varies according to infrastructure sector. With this paper, our goal is to provide a comparative analysis of systems engineering (SE) and asset management (AM) best practices from the past 10 years. Specifically, we aim to show that the International Standards Organization (ISO) 15288

[4] The contents of this appendix were submitted and accepted for publication as a conference paper by Valencia, Colombi, Thal, and Sitzabee. The paper is titled "Asset management: A systems perspective" and appears in the *Proceedings of the 2011 Industrial Engineering Research Conference* held in Reno, NV.

processes, as described in the 2010 INCOSE Systems Engineering Handbook (v3.2) (Haskins, 2010), can be applied to the engineering management of infrastructure.

A.2 Infrastructure Asset Management

There are many ways to define infrastructure asset management. For example, the U.S. Department of Transportation defines asset management as a systematic process for maintaining and operating physical assets cost-effectively through a combination of engineering principles and sound business practices (U.S. DOT, 1999). Similarly, the Transportation Asset Management Guide (Cambridge Systems Inc, 2002) considers the core elements of asset management to center on the process of resource allocation to effectively manage assets. The elements of this process consider the following tenets: an approach that is policy driven, options and trade-offs analyses, effective service and project delivery, decision-making based on quality information, and continuous monitoring of the information base for feedback into updates and improvements. Hoskins, Brint, and Strbac (1999) describe asset management as activities for the upkeep of a given infrastructure system such as inspection, maintenance, repair, and replacement of parts of the system network all at minimum cost. Finally, Grigg (2003) synthesizes an asset management definition as "an information-based process used for life-cycle facility management across organizations." He goes on to write that important features of the definition include an "assets" view of the infrastructure system and its components, life-cycle management, enterprise-wide use of asset management, and the use of information-based processes and tools.

The common themes among the varying definitions lead us to offer our own definition: "Asset management is the holistic assessment of a given infrastructure system using a life-cycle approach based on quality data for the purpose of optimally managing physical assets at least cost to stakeholders." This definition recognizes several themes. First, there is a growing acknowledgement within the infrastructure industry that a holistic, life-cycle view, or systems view, can provide the tools and techniques needed to address infrastructure issues. Second, it recognizes the purpose of asset management can only be realized with quality data about the infrastructure system. Finally, the definition identifies that asset managers have a duty to minimize cost to stakeholders. These costs are not only fiscal constraints on operating budgets, but should be inclusive of the entire life-cycle cost of the system as well as intangible costs such as environmental health, loss of public trust, and other social costs.

A.3 Systems Engineering

Similar to asset management, many authors have provided varying definitions of systems engineering (Blanchard & Fabrycky, 2011). However, the International Council on Systems Engineering (INCOSE) has published a handbook that offers a description from the synthesis of three definitions (Haskins, 2010):

> Systems engineering is a discipline that concentrates on the design and application of the whole (system) as distinct from the parts. It involves looking at a problem in its entirety, taking into account all the facets and all the variables and relating the social to the technical aspect (FAA, 2006).
>
> Systems engineering is an iterative process of top-down synthesis, development, and operation of a real-world system that satisfies, in a near optimal manner, the full range of requirements for the system (Eisner, 2002).
>
> Systems engineering is an interdisciplinary approach and means to enable the realization of successful systems. It focuses on defining customer needs and required functionality early in the development cycle, documenting requirements, and then proceeding with design synthesis and system validation while considering the complete problem: operations, cost and schedule, performance, training and support, test, manufacturing, and disposal. SE considers both the

> business and the technical needs of all customers with the goal of providing a quality product that meets the user needs (INCOSE, 2004).

When considering common themes of systems engineering from the handbook and other works, it is clear that asset management and systems engineering share many of the same core concepts. For example, a life-cycle approach taking a holistic view is central to both SE and AM. Recognition that stakeholders determine value of the outputs of the system is another shared theme between the two fields. Optimal design, operation, and management of a system through informed decision-making are also goals shared by both fields.

A.4 The Need for a Systems Perspective

Many researchers and practitioners contend that traditional infrastructure management approaches are no longer effective. Godau (1999, 2004) makes this claim due to complexities from technology and other external factors such as economics, politics, and the environment. Robinson, Woodard, and Varnado (1998) echo the need for change as infrastructure systems are now more interconnected than ever. The American Society of Civil Engineers, through in-depth roundtable discussions, found that a common thought among discussion participants was the need to take a systems approach towards the nation’s infrastructure (Powell, 2010). The underlying premise held by these researchers and practitioners is that a systems orientation will help solve problems encountered in the management of infrastructure.

Indeed, some within the SE field feel that the profession can serve as a framework for engaging in this problem. Cook and Ferris (2007) write that SE, as a multi-methodology, is an appropriate way to solve traditionally non-SE problems provided that the solution will be technical in nature. INCOSE itself has developed an Infrastructure Systems Working Group (ISEWG) whose membership is concerned with the application of the discipline of SE to physical infrastructure. The ISEWG published a special infrastructure issue with its editor stating (Jackson, 2004):

> "individual infrastructures, as well as the collective infrastructure, obey all the rules of systems. They are all collections of assets, the subsystems, which individually and collectively perform functions ... they can be considered a system of systems (SoS) since they interact with each other."

The special issue goes on to highlight the SE applications to infrastructure such as rails (Williams et al., 2004), highways (Krueger, 2004), water (Doukas, 2004), and energy (Bauknight, 2004). All contributing authors to this issue conclude that SE undoubtedly has applications to infrastructure asset management.

The application of SE provides benefits to the field of asset management. One such benefit is the understanding of system interfaces as the definition and management of these interfaces is central to SE – it is the interactions of the parts that produce the results desired out of the system (Maier & Rechtin, 2002). At the design stage, a systems approach will generate a greater understanding of not just the desired end-product, but also the problem at hand potentially leading to a superior system. Finally, during operations and maintenance, infrastructure managers taking a systems view and holistic decision-making approach might see reduced failures, reduced system risk, optimized functionality, and optimized maintenance cost – which are benefits addressed in the papers reviewed for this study.

A.5 Comparative Analysis of SE Processes and Asset Management Practices

As previously stated, not all SE tools, techniques, and procedures are directly applicable to the field of asset management. In fact, Godau (2004) suggests that SE should be tailored to match infrastructure specific problems. With this in mind, of the 25 systems engineering processes and life-cycle stages specified by ISO 15288:2008, we highlight six of these processes and demonstrate their applicability to the needs of infrastructure managers. The remainder of the paper relates these six SE processes to asset management practices and research found in the literature. As a starting point, the International Infrastructure Management Manual (IIMM) (Roberts et al., 2006) is referenced against the process descriptions outlined in the INCOSE Handbook (v3.2) (Haskins, 2010). Practices and applications in the literature are used to illustrate the SE process concepts in use. Figure A1 illustrates the direct comparisons of the SE processes to be investigated to broad processes of asset management.

Systems Engineering		Infrastructure Asset Management
Stakeholder Requirements Definition Process	↔	Levels of Service
Decision Management Process	↔	Optimized Decision-making
Risk Management Process	↔	Risk Assessment and Management
Information Management Process	↔	Information Systems and Data Management
Measurement Process	↔	Measure Levels of Service
Life Cycle Management Process	↔	Life Cycle Asset Management

Figure A1. Comparison of six SE processes to six AM processes.

A.5.1 Stakeholder Requirements Definition Process.

The first steps in establishing asset management processes are similar to the first steps in systems engineering. In SE, the initial phase of any given product is to determine stakeholder requirements which, in turn, drive system development. For asset managers, given that infrastructure systems are already in place, and once asset inventories have been established, their objective in defining stakeholder requirements centers on establishing levels of service (Roberts et al., 2006). This process involves segmenting the customer base into identifiable groups and then understanding what these customers value. This is necessary because, just as in SE, the differing values, agendas, needs, and interests of the various stakeholders are used to judge the efficacy of the organization. For SE, organizational efficacy is measured against the final product delivered; for AM, this is judged by the level of service provided.

The question of how to determine the appropriate level of service is a topic addressed by a number of researchers. Rogers and Louis (2008) and Ramesh and Narayanasamy (2008) explore this question with regards to water service. The former studied community water systems in the U.S. and the latter rural water delivery in India. Both found that system inefficiencies resulted from decision-makers failing to properly account for stakeholder requirements. Specifically, Rogers and Louis contend that typical decision approaches lead to short-term positive impacts for the immediate community (i.e., increased economic activity through capital improvements) but potentially result in negative long-term impacts (i.e., system deterioration because of deferred maintenance). Ramesh and Naraynasamy find that in failing to recognize the lack of technical capability for municipalities in operating and maintaining water infrastructure, the Indian government has provided excessive infrastructure which has resulted in excessive water waste across the country. Rogers and Louis offer that a systems analyses approach could help in bringing appropriate levels of service from community water systems.

Work in the transportation sector concerning levels of service also begins with assessing stakeholder requirements. Yin, Lawphongpanich, and Lou (2008) provide an approach that estimates the necessary investment for maintenance and repair of highway networks to maintain or increase levels of service. Their mathematical model accounts for user preferences when deciding routes and factors in unknowns such as travel demand and asset deterioration. They report that their model presents solutions that provide equivalent levels of service as compared to conservative investment plans but at a much lower investment cost. Similarly, Yang, Bell, and Meng (2000) present a model that determines appropriate road capacity and levels of service by also accounting for route choice behavior of travelers.

A.5.2 Decision Management Process.

Another key process for AM and SE practitioners is the decision management process. The definitions in the two fields are similar in that the process involves selecting the optimal decision among a number of alternatives. Other similarities in this process include utilization of classical decision-making approaches, namely risk-based and multi-criteria decision-making, and the use and development of decision-making models.

Both fields recognize that there are two broad types of decision-making approaches: risk-based decision-making and multi-criteria decision-making (Blanchard & Fabrycky, 2011; Roberts et al., 2006). The risk-based approach quantifies the alternatives and, combined with the likelihood of an outcome, leads to the basis of a decision. Even though the IIMM emphasizes cost as the primary means for quantifying alternatives, other asset management studies use different methods for quantification. For example, Seyedshohadaie, Damnjanovic, and Butenko (2010) use the idea of risk as a basis for maintenance approaches on transportation infrastructure. Asset management has wide-ranging stakeholders with varied agendas and so intangible impacts are significant to asset managers. The multi-criteria decision method seems to be able to address intangible impacts and there are a number of works that present multi-criteria decision methods in transportation (Iniestra & Gutiérrez, 2009; Rybarczyk & Wu, 2010), facility management (Montmain, Sanchez, & Vinches, 2009), waste management (Hokkanen & Salminen, 1997; Vego, Kučar-Dragičević, & Koprivanac, 2008), and energy (Mills, Vlacic, & Lowe, 1996).

Given these decision-making approaches, decision-making models are a necessary component to the process. Blanchard and Fabrycky (2011) suggest that decision-making models and simulations are useful tools in the process as they enable the study of the system at far less cost and with far less time compared to direct observation of the system. The use of decision models are widely used in asset management. Fenner (2000) reviews decision methodologies in the water/wastewater sector and finds that current models lead to maintenance activities only on the highest risk or most critical sewers. He suggests a change in established decision methods is needed so that maintenance activities are carried out that affect the wider catchment system. He also reviews promising developments in his field such as non-critical sewer assessment, sewer survival models, usage of performance indicators, risk analysis through sediment build-up, and rehabilitation cost analysis, but finds that a lack of data prevents meaningful analysis of options by municipalities. Similarly, Hoskins et al. (1999) suggests that changes to electricity industry decision models are necessary and presents a decision approach that recognizes the constraints of limited budgets. Claiming to be generalizable to other infrastructures, their six-step approach is contingent on the ability of managers to quantify and model the condition of a component, relate the component to the overall system, and then model the component's deterioration over time. This approach promises to lead asset managers to more informed decisions; however, much like Fenner (2000), Hoskins et al. finds that the availability of data limits the quality of decisions.

A.5.3 Risk Management Process.

There is considerable overlap in how asset management and systems engineering treat risk management. Both the SE Handbook and IIMM provide similar outlines for the risk management process with key steps including setting the risk context, identifying the candidate risk, analyzing each risk, developing risk treatment strategies, and continuous monitoring and review of the risk management process (Haskins, 2010; Roberts et al., 2006). Additionally, both sources define risk in the same manner and that risk is composed of the likelihood an event will happen and the consequence of that event happening. Finally, both advocate the use of risk rating tables to visually depict the magnitude of a given risk.

Although the considerable overlap suggests that risk management is a well-developed concept in SE and AM, several studies offer insights that may allow even greater incorporation of risk management into the asset management process. For example, Piyatrapooni, Kumar, and Setunge (2004) suggests the use of risk maps that synthesize individual risks onto a single graph and categorize each risk event into one of three "tolerability regions." Risk mapping could then be incorporated into the decision-making process to lead to more confident decisions by asset managers. Austin and Samadzaeh (2008) propose a novel metric for systems engineers to measure the effectiveness of a risk management system. They found that a large body of literature exists which evaluate different risk management systems, but found that the literature did not offer a "risk management effectiveness" metric. They propose a measure of effectiveness metric with the aim to contribute to the improvement of the overall SE risk management system. This metric is fully applicable to asset management systems. Specific applications of risk management principles in differing sectors of infrastructure include applications in facility management (Taillandier, Sauce, & Bonetto, 2009), water infrastructure (Pollard, Strutt, Macgillivray, Hamilton, & Hrudey, 2004; Rogers & Louis, 2008), transportation (Mansouri, Nilchiani, & Mostashari, 2010; Seyedshohadaie et al., 2010), and energy (Bertolini, Bevilacqua, Ciarapica, & Giacchetta, 2009; Nordgård & Sand, 2010).

A.5.4 Information Management.

The SE information management process is the overall process that ensures relevant information is collected, available in a timely manner, valid and complete, and accessible through an archived database of information (Blanchard & Fabrycky, 2011). Asset managers recognize the need for information management systems (Halfawy, 2010; Rasdorf et al., 2009; Sitzabee, Rasdorf, Hummer, & Devine, 2009; U.S. DOT, 1999). The IIMM provides characteristics of good asset management systems which include proper information architecture, ease of upgrades and expansion, ability to integrate data across platforms, adequacy of information technology support, and sufficient resources provided by the organization to support the information management system (Roberts et al., 2006).

Examples of information systems used by asset managers are geographic information systems (GIS) which relate geospatial data to specific components of an infrastructure system, maintenance management systems (MMS) which store and manage information regarding an organization's maintenance activities, and pavement management systems (PMS) and bridge management systems (BMS) which are used extensively in the management of U.S. roads and bridges. These and other tools like them enable the collection and analysis of asset data and are central to effective asset management processes (U.S. DOT, 1999). In addition to data collection and analysis, other key components of these systems include feedback and update mechanisms, analytical models, and built-in processes which identify and recommend capital improvement, maintenance, and repair investment strategies. The use of information management systems has been proven to increase management effectiveness (Burns, Hope, & Roorda, 1999; U.S. DOT, 1999); however, the increasingly complex, interdependent nature, and data availability on today's infrastructure systems present a data management problem in the form of data integration for asset managers.

Much like SE, information system data integration is of importance to asset managers because poor integration results in organizational inefficiencies and suboptimal decision-making (Halfawy, 2010; Rasdorf et al., 2009). Problems of current information processes include: (1) data storage within "silos" resulting in duplication and inconsistencies, (2) data errors resulting from translation and re-entry into different systems, (3) data source fragmentation which creates difficulties in generating comprehensive views, and (4) an overall, highly inefficient information management system (Halfawy, 2010; Rasdorf et al., 2009). Data integration is not a new field of study in AM as the past two decades include works addressing this problem (Halfawy, 2010; Shen et al., 2010). However, these works report that asset managers are behind other fields in addressing this problem due to organizational fragmentation across industry and government. Organizational fragmentation leads to data fragmentation and presents a serious challenge in data integration. Given information's central role in asset management, it is imperative that data integration be taken into account when developing AM information systems.

A.5.5 Measurement Process.

Tied to the information management process is the measurement process. The measurement process as defined by INCOSE is the collection, analysis, and reporting of data on product performance and organizational processes which support management decision-making and contribute towards performance improvement of the system (Haskins, 2010). Similarly, asset managers collect performance measures for the comparison of system performance to levels of service. The IIMM categorizes these measures into two types: asset condition states and system performance (Roberts et al., 2006). Two particular concerns are the ability for asset managers to provide accurate measures of condition states and the ability to determine future performance of infrastructure systems.

Asset condition states and system performance do not necessarily have direct relationships with each other (Roberts et al., 2006). A degraded asset may or may not lead to degraded system performance and degraded system performance is not necessarily indicative of degraded assets. For example, water pipes with severe corrosion could still function properly in transporting water. Alternatively, a poorly functioning electrical grid does not necessarily point to inefficiencies from degraded substations, electrical lines, transformers, or other assets. Such cases could be caused from operator error or severe weather. However, a failed condition state of an asset would undoubtedly lead to performance failure. So although the metric of interest is system performance, asset condition states must also be measured to prevent system performance failure. Of interest in the literature is the use of remote sensors for structural health monitoring of civil structures such as bridges and buildings (Chang, Flatau, & Liu, 2003; J. P. Lynch, 2004; J. Lynch, 2007). These researchers explore recent developments in the design and use of sensor technology given its low cost and accessibility as compared to currently practiced and labor-intensive visual inspections. In general, they find that the technology has proven valuable in detecting substantial damage caused by a single, disruptive event, but further work is needed to develop sensing methods for early stages of damage caused by gradual deterioration.

Condition states by themselves are only useful to asset managers in providing the current condition at a given point in time. More useful to asset management is the ability to predict component performance, which would lead to system performance forecasts. Therefore, this component modeling is of particular interest, specifically mathematical models which provide a means of predictive assessment for a particular asset (Abu-Elanien & Salama, 2010; Ching & Leu, 2009; Sitzabee et al., 2009). Because of the great variety of asset types, techniques for condition asset measurement vary greatly. For example, Sitzabee, Rasdorf, Hummer, and Devine (2009) document the process of gathering data for low-value/high-volume assets (road markings) through visual inspection and random sampling. Abu-Elanien and Salama (2010), on the other hand, gather data for transformers (high-value/low volume assets) and do so through inspection of each individual asset and with techniques beyond visual inspection. Mathematical deterioration models are applied using condition assessments and other factors and the results of such models are considered by asset managers as they construct their respective maintenance plans or make key decisions in maintenance and repair activity.

A.5.6 Life-Cycle Model Management.

Finally, the issue of life-cycle model management for asset managers is addressed. As defined in the INCOSE Handbook, life-cycle model management is an organizational process that creates life-cycle models as a basis for common reference to a project's life-cycle (Haskins, 2010). Additionally, feedback mechanisms from this process are generated for systems engineers to determine if the organization is following its own management process and adjustments are made accordingly. The IIMM considers life-cycle models similarly but focuses more on the operations and maintenances phases of the system life-cycle (Roberts et al., 2006).

As such, two views, a global systems view or component level view, can be taken of asset life-cycle. First, a global system view can be taken of the entire system usually to understand overall system life-cycle costs (LCC) or life-cycle value (LCV). A review of published case studies shows successful implementation of LCC in the facility construction, energy, and transportation sectors (Korpi, 2008). Kim et al. (2010) demonstrate its applicability by developing an LCC estimate for light rail transit. The objective for conducting these analyses is to achieve the lowest long-term costs in system operation and maintenance rather than choosing alternatives that result in short-term savings (Roberts et al., 2006). Unfortunately, policy makers typically gravitate towards the latter approach which results in increased future risk due to deferred maintenance and repairs. Slightly different from LCC is the idea of measuring and quantifying value in LCV which places emphasis on stakeholder requirements, both present and future. Some argue that analyses of LCV lead to better designed systems since perceived value changes with stakeholders over time (Browning & Honour, 2008). Developing a system that can endure these changes will lead to a more valuable system and they illustrate their case with the development of the U.S. cellular infrastructure.

An alternative view of life-cycle can be taken at the component level of a system for the purpose of analyzing component performance. Abu-Elanien and Salama (2010) apply asset management modeling techniques on electrical transformers in order to determine performance degradation over time. Their approach is mimicked for other electrical distribution assets as demonstrated by Hoskins et al. (1999) for oil-filled circuit breakers. The implications from these component models are applicable to the greater energy distribution system since these are critical components to the larger systems. Component life-cycle analyses such as these are necessary inputs used in various asset management decision processes and contribute data to system life-cycle costs, as already discussed.

Finally, the SE Handbook specifies that life-cycle model management should include a feedback mechanism for regular review of its processes. Asset management holds this component of life-cycle management in much the same way. Without doing so, asset management organizations risk misalignment of its management processes with strategic objectives, legal and regulatory requirements, and customer expectations (Roberts et al., 2006; U.S. DOT, 1999)

A.6 Conclusion

This paper has provided a comparative analysis of systems engineering and asset management practices found in the literature from the past 10 years. Researchers in the field of systems engineering and asset management assert that SE processes can be applied to asset management and this paper explores that claim. Six processes described in the SE INCOSE Handbook are elaborated. Specifically, the processes of stakeholder requirements definition, decision management, risk management, information management, measurement, and life-cycle model management are viewed as having direct applicability to the AM field and examples of their application are illustrated by various works in the asset management and systems engineering literature. In fact, the need for a systems approach to infrastructure asset management has been highlighted by practitioners in the field. Systems engineering researchers have found that SE practices are applicable to areas outside their expertise and the increasingly complex and interconnected nature of infrastructure systems make it suitable for application of the SE discipline. However, application of systems methods, processes, and techniques is found to be limited and the techniques vary according to infrastructure sector. Nevertheless, continued crossover of SE processes and techniques into the field of asset management hold promise for greater effectiveness in the management of infrastructure systems.

Appendix B. Literature Review on Simulation and Modeling Methods in Critical Infrastructure Protection

This appendix provides an overview of the modeling and simulation methods found in the infrastructure protection literature. The work presented here provided a starting point in the modeling of infrastructure systems by narrowing the choices of possible methods to a small group of four. These four groups of modeling methods are presented through a discussion of various work found in the literature.

B.1 Introduction

Critical infrastructures are systems and assets so vital to the United States that their disruption will lead to severe consequences for the country's national security, economy, or public health and safety (U.S. Department of Homeland Security, 2009). Critical infrastructures are highly interconnected systems and in which the inherent relationships represent a new and rapidly growing area of study (Satumtira & Dueñas-Osorio, 2010). Authors have characterized the different types of infrastructure interdependencies (Haimes et al., 2007; Rinaldi et al., 2001) and others have researched ways to model and simulate infrastructure behavior as a result of these interdependencies (Bagheri & Ghorbani, 2008; Brown, 2007; Pederson et al., 2006). This work provides a general taxonomy of the most prevalent critical infrastructure simulation and modeling techniques. First, a background into network interdependencies of critical infrastructure systems is offered and then four interdependency modeling classes are proposed and explained.

B.2 Background

Infrastructure systems provide essential goods and services to people and, as such, are the basic underpinnings of modern society. These systems are typically ignored and taken for granted until there is some sort of system failure (Roberts et al., 2006) which results in a loss or degradation of service. The work of protecting these systems is important to the continuous functioning of society and professional organizations and governments are attempting to call to light the importance of infrastructure. For example, the American Society of Civil Engineers has been publicly acknowledging the degraded state of the U.S. infrastructure system (Powell, 2010) and the U.S. government has been working since the early 1990s on protecting these infrastructures at the national level (President's Commission on Critical Infrastructure Protection, 1996).

The events of 9/11 spurred interest and focus on critical infrastructure protection. The Department of Homeland Security was formed shortly after 9/11 and was charged with developing the National Infrastructure Protection Plan (NIPP). The NIPP provides the framework for coordinating national efforts to protect infrastructure from damage or destruction through deliberate efforts (such as a terrorist attack), natural disaster, or some sort of other emergency (U.S. Department of Homeland Security, 2009). As with all broad and far-reaching objectives, the efforts in meeting this goal vary greatly and one such area of work is in the simulation and modeling of these infrastructure systems.

Infrastructure systems are highly interconnected systems within themselves (components are networked together to function as a single system) and to other systems (outputs from one system are inputs to another). These interconnections, whether internal or external, create system behaviors that can be predicted if modeled or simulated correctly. The results from predicting infrastructure behavior after a disruptive event can result in policies and initiatives which better protect these systems. Because individual infrastructures are not stand-alone entities and require other infrastructures to function, the idea of infrastructure interdependency, and the risks resulting from these interdependencies, is an actively researched and growing field (Satumtira & Dueñas-Osorio, 2010).

In their seminal work, Rinaldi, Peerenboom, and Kelly (2001) provide basic definitions to facilitate the discussion of infrastructure interdependencies. First, they establish the difference between the terms *dependency* and *interdependency*. An infrastructure dependency is a relationship between two infrastructures which is uni-directional. That is, one infrastructure relies on the output of a different infrastructure (or multiple infrastructures) and this relationship is not reciprocal. An infrastructure interdependency is a bi-directional relationship between two or more infrastructures where the infrastructure outputs are mutually relied upon by the infrastructure systems involved. In other words, an interdependency exists when systems are dependent on each other. Conceptually simple, the notion of interdependency increases the complexity of a system, and this complexity creates behaviors within the "system of systems" that are not intuitively predictable. These complexities and behaviors are the interest of researchers studying the field of infrastructure interdependencies.

Rinaldi et al. (2001) go on to formulate a six-dimension framework of infrastructure interdependencies important to the field of infrastructure protection research, but this paper will provide a brief overview of just one dimension – interdependency types. Haimes et al. (2007), McNally et al. (2007), and Johansson and

Hassel (2010) provide similar classification schemes and the differences within the lexicon are indicative of a still growing field. Figure B1 shows these three classifications graphically. Rinaldi et al. (2001) establishes that four types of interdependencies exist: physical, cyber, geographic, and logical. Physical interdependencies are relationships based on material outputs from one infrastructure being passed to another as a material input. Cyber interdependencies exist when information is the entity being passed between infrastructures. Geographical interdependencies are based on physical proximity, e.g., infrastructures are located such that a localized event affects the status of these infrastructures. Finally, logical interdependencies exist when there is a bi-directional relationship and this relationship is neither physical, cyber, nor geographical. (For an example, see Rinaldi et al.'s (2001) explanation on California's electricity/financial market logical interdependency.)

A variation of Rinaldi et al.'s (2001) work incorporates economic interdependencies. Haimes et al. (2007) also describes four interdependency types of physical, logical, information, and economic couplings. Physical, logical, and information couplings are similar to the above definitions of physical, logical, and cyber interdependencies; economic couplings are introduced. (In his work, Haimes uses the term "couplings" rather than interdependency, a sign that the study of infrastructure protection is still a new field). Economic couplings attempt to predict the economic behavior of either a region or economic sectors as a result of interdependencies and economic inputs and outputs. Regional economic couplings are similar to geographic interdependencies by spatially bounding the economy of interest. Inter-sector economic couplings address the linkages of entire economic sectors without the limits of geography. This input-output view of infrastructure interdependency is useful in predicting post-disaster effects on economies of interest and is the basis of a major modeling and simulation technique in infrastructure interdependency, discussed later in this appendix.

Finally, McNally et al. (2007) and Johansson and Hassel (2010) offer a simpler framework for infrastructure interdependency. In attempting to synthesize geographic interdependencies with Rinaldi et al.'s (2001) three other types, these works propose that interdependency classifications be even more generally classified into two broad categories: functional and spatial. They propose functional interdependencies to encompass Rinaldi et al.'s (2001) three classes of physical, cyber, and logical interdependencies while spatial interdependencies receive the same treatment as geographical interdependencies.

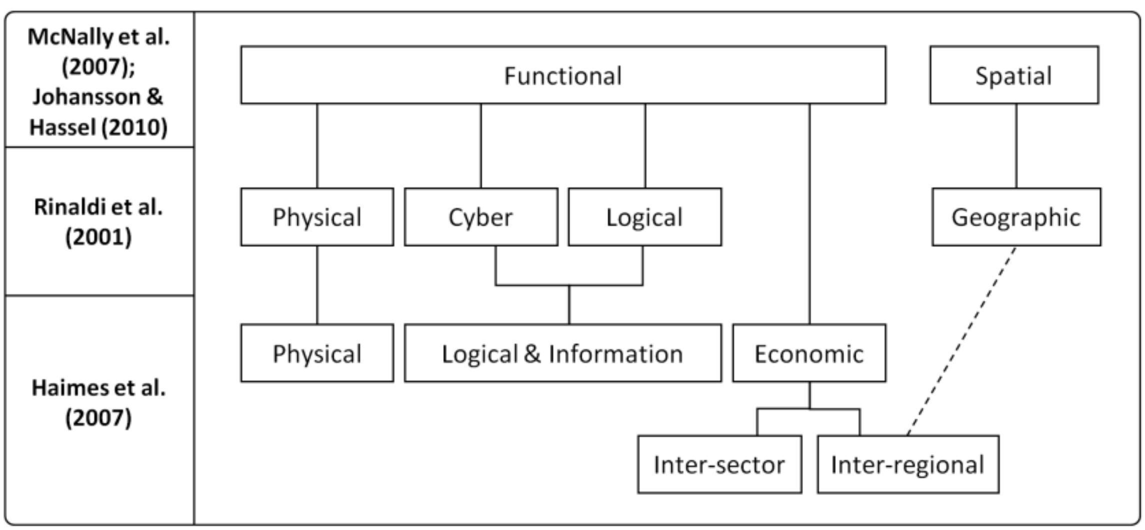

Figure B1. Graphical comparison of three interdependency classification schemes.

The interdependency types are important to understand as these contribute to differences in relationships within and across infrastructures. For example, when dealing with time scales, transactions based on cyber and logical interdependencies occur in very short cycles compared to physical transactions. As another example, spatial and functional interdependencies differ from each other as spatial interdependencies are static (infrastructures typically do not move) whereas functional interdependencies are dynamic. Understanding the differences between the interdependency types is necessary in building accurate and realistic models and simulations. Four different classes of modeling and simulation methods are briefly described in the next section.

B.3 Simulation and Modeling Classifications

Within the field of critical infrastructure interdependency simulation and modeling, researchers have proposed many different tools and methods in order to better understand infrastructure behaviors and plan for their protection. Several works have synthesized the literature by listing specific tools and methods. Specifically, the works by Cummings et al. (2006), Pederson et al. (2006), and Bagheri & Ghorbani (2008) provide insight to the current state of the literature by providing lists of the "state of the art" in critical infrastructure modeling and simulation. Although these works are comprehensive in nature, greater abstraction of critical infrastructure modeling and simulation into broad categories is necessary to provide a basic understanding of the state of the field. A taxonomy of critical infrastructure simulation and modeling techniques will help in identifying theoretically similar tools and methods, while at the same time providing a means for identifying new tools and methods. In the most detailed and comprehensive work covering the literature, Satumtira and Duenas-Osorio (2010) present a study that suggests the taxonomy consist of four classes.

B.3.1 Input-output inoperability Model (IIM).

Based on economist Leontief's work of economic interdependencies, the Input-output inoperability Model (IIM) simulates the inter- and intra-connectedness of infrastructure systems by modeling the "risk of inoperability" of a system as an input or output to other systems. The risk of inoperability is an expected value based on the likelihood (probability) of inoperability. Inoperability is expressed as a value between 0 and 1, where zero denotes no inoperability (flawless operation) and 1 denotes complete inoperability (complete failure). A matrix is developed which correlates these inoperability expected values to interconnected systems; through matrix algebra, the inoperability of the entire system (or subsystem) can be simulated when a disturbance is introduced.

The benefit of this simulation method is threefold. First, since the IIM is a mathematical model, no specialized modeling software, and associated costs and time for training, is needed. The basic matrix algebra can easily be completed on standard spreadsheet applications. Second, mathematics leads to quantifiable effects of disruption through the system under study and this quantification leads to better investment strategies for infrastructure protection (Crowther & Haimes, 2005). Through the IIM, decision-makers will have an objective means for comparing one protection strategy over another. Finally, the IIM can be scaled to different levels of interest. The method can be scaled up to explore macro-economic effects or scaled down to a local or plant level to discover disruption cascades at these lower levels.

The level of detail necessary in developing an IIM simulation is its primary limitation. To accurately predict a system's interdependent behavior, the inoperability values that are transmitted between infrastructures must be determined. Unlike the macro-economic level, which may use data from the U.S. Bureau of Economic Analysis, lower levels of simulation require extensive data collection to determine appropriate values. A second limitation with the IIM method is its applicability in analyzing events immediately after a disruptive event. Crowther and Haimes (2005) report that this model is most appropriate for systems operating in equilibrium since a chief assumption is an inherent stability of interdependency between systems. Results of an introduced perturbation should then only be interpreted as a new equilibrium for these systems.

In response to these limitations, two extensions and adaptations have been developed. Dynamic IIM (DIIM) and the Multi-Regional IIM (MR-IIM) attempt to address the temporal and geographical aspects of a disaster (Haimes et al., 2007). The DIIM has the ability to describe effects of recovery immediately after a disaster. It also incorporates the concept of system resilience, a concept lacking in the IIM. MR-IIM has the ability to model impacts across multiple regions through the use of geospatial databases. Further exploration of these two models is worth additional study as their development could lead to better decision-making tools for infrastructure policy-makers.

B.3.2 Agent-Based Modeling (ABM).

Agent-based modeling is a new approach in modeling complex systems and is applicable in a wide variety of fields (Bonabeau, 2002; MacAl & North, 2010). This theoretical framework is based on the idea that a system is composed of individual agents acting independently and that these actions result in an emergent behavior of the overall system. Researchers have demonstrated that ABM is an appropriate tool for simulating infrastructure interdependency behavior (Amin, 2000, 2001; Brown, 2007; Cardellini, Casalicchio, & Galli, 2007; Panzieri, Setola, & Ulivi, 2004).

Macal and North (2010) outline the three essential elements for a typical agent-based model. First, there must be a set of agents that are described with attributes and behaviors through specific algorithms. Infrastructure decision-makers and control mechanisms would be these agents. Second, there must be relationships between agents. Given the networked nature of infrastructure interdependency, these relationships are innate with the problem under study. Third, the environmental setting must be identified as agents which also interact with their environment. For example, infrastructure policies at differing governmental levels could be modeled as discrete agents.

When complete, an ABM may provide counter-intuitive system behaviors or illustrate new system equilibriums. Bonabeau (2002) outlines that the ability to capture emergent system phenomena is one of the three ABM benefits. The other two are a "natural description" of the system and ABM's flexibility in modeling across different system dimensions. Natural description refers to the "bottom-up" technique of describing the system. The modeler looks at the system from its discrete components at the lowest levels (rather than at a high level of abstraction) and formulates the agent behavior from the agent's point of view. This frame of reference results in a simulation that captures what an agent actually does and, thus, is more natural. The flexibility in ABM is realized when there is a need to scale up or down the simulation. For example, the number of agents can easily be increased or decreased, the level of system abstraction (e.g., modeling granularity) can also be increased or decreased, or the details of the agents themselves can be more detailed or generalized. This flexibility is helpful when certain system details are not known, which can be the case for large scale systems, and modifications to the model are necessary for its usefulness.

B.3.3 Network (Graph Theory) Methods.

Equally new in the field of infrastructure interdependency is the application of network analysis, known as graph theory in mathematics, to infrastructure interdependency simulation and modeling (Satumtira & Dueñas-Osorio, 2010). This branch of mathematics uses nodes and edges to define relationships (edges) between objects (nodes). Much like in ABM, the interconnected nature of infrastructures naturally lends itself to this type of analysis. Nodes represent discrete units within and across infrastructures that consume or produce resources, and edges represent the path that these resources take to and from nodes. The representation of these interconnections form the system's topology and with this structure, graph theory modelers attempt to capture system performance and risks. Indeed, Duenas-Osorio, Craig, and Goodno (2004) highlight that one of the major objectives of graph theory in infrastructure research is the ability to predict a system's behavior based only on topology, disruptions introduced, and the rule sets that govern nodes and edges.

Osorio, Craig, and Goodno (2004) also provide a brief discussion on the pertinent properties of network topologies and variations of network models within graph theory. With regards to network topologies, topological properties provide modelers insight into the degrees of connectedness of an infrastructure. These elements can describe the global, local, and even randomness of connections within the system. By understanding these statistical properties, comparisons may be made between model variations or real-world networks for better understanding or more realistic modeling. Regarding network models, Osorio, Craig, and Goodno (2004) and Lewis (2006) highlight different graph theory modeling types as applied to infrastructure interdependency. The emergence of applying graph theory to infrastructure research is evident and both works indicate a further need for research which addresses the validity of graph theory in this application. However, the literature is not without examples of such work. Applications of graph theory models addressing interdependency include natural gas and power generation (Nozick et al., 2004) and water and power distribution (Dueñas-Osorio, Craig, & Goodno, 2007; Dueñas-Osorio, Craig, Goodno, & Bostrom, 2007).

B.3.4 Other Modeling Types.

This final category attempts to capture the simulation and modeling types that do not fit in the three above major categories, but have some presence in the literature worth mentioning. Systems dynamics and social network analysis have been used to analyze interdependency vulnerability but have yet to gain traction as major modeling and simulation types within the field. What follows is a brief explanation of the two methods.

Systems Dynamics. Systems dynamics is a simulation approach that attempts to create a better understanding of complex systems by modeling the interconnections of elements through feedback loops and stocks and flows of resources. This method often leads to counter-intuitive, non-linear results of system behavior. Work at the National Infrastructure Simulation and Analysis Center highlight several infrastructure simulations based on this method (Brown, Beyeler, & Barton, 2004; Brown, 2007). These models are able to show system limitations based on system storage capacities, broad policy effects on systems under study, and supply and demand effects.

The ability to show these types of results are somewhat different than the other major simulation modeling types. Systems dynamics offers a more temporal perspective of system vulnerability, whereas IIM, ABM, and network graph theory work with a more static view of the system. The holistic and dynamic modeling process central to systems dynamics offer key insights into the system under study. The necessary system aggregation to do this, however, is a limitation to this modeling type. Modeling analysts must be able to take a high-level perspective of the system in question; therefore, lower level details may be ignored or assumed. The process of creating these assumptions must be carefully done; otherwise, the results of the model may be rejected by the intended audience.

Social Network Analysis. Social network analysis is a method of analysis that examines the relationships of entities of a network and reveals patterns and implications within the network (Wasserman & Faust, 1994). Chai et al. (2008) used this method to show the relative importance of specific infrastructures suggesting that policy could be shaped to protect the top-most systems. Brown (2007) simulated the impacts of an influenza pandemic and used social network analysis to suggest policy to better protect a community. This type of analysis is predominantly applied in social science research, but the interconnections of infrastructure systems allow for this type of analysis. Although there is evidence of its applicability, the critical infrastructure protection studies using social network analysis have yet to gain traction within the literature.

B.4 Conclusion

This work presented the results of a literature review into critical infrastructure modeling and simulation. A taxonomy of four broad techniques was created: input-output inoperability modeling, agent-based modeling, network (graph theory), and other. This taxonomy is useful in understanding the state of the literature on the modeling and simulation techniques of critical infrastructures. The area of critical infrastructure protection remains a growing field and the characterization of the current modeling and simulation methods brings some clarity to this area of research.

Appendix C. Procedure Logs and Notes on Topological Cleaning for Geographic Information System Data

This appendix contains an excerpt of procedure logs and notes taken during the data analysis portion of the research. A geographic information system (GIS) procedure log is a document which outlines the actions a GIS operator has taken in processing the workflow for a particular project. A procedure log is helpful in that it provides a guide for future reference to other GIS operators so that analysis and cartographic products can be replicated. Due to the size of the existing log, this appendix does not provide the complete record for the GIS processes implemented in this dissertation. Instead, it provides the portions of the log, as well as the research notes, which directly relate to the topological cleaning necessary to make the data usable. Data topology was discovered to be an issue in that the lack of, or inconsistencies in, topological connections prevented any analysis from being conducted. Therefore, extensive data preparation was necessary for the data used in this research. This chapter is divided into seven sections constituting six separate entries in the log and a conclusion summarizing this appendix.

C.1 Initial Work with the GIS Dataset

(10 June 2013) On set-up of the initial ArcMap document, import data from the source .mdb file. Figure C1 provides the feature datasets and accompanying feature classes that were imported.

base_data **Description:** Contains the installation boundary, facilities, parking and roads **Feature classes:** structure_exisiting_area, road_area, vehicle_driveway_area, vehicle_parking_area, installation_area	**utilities_gas** **Description:** Information on the natural gas distribution system **Feature classes:** nat_gas_reg_reducer_point, natural_gas_meter_point, natural_gas_tank_point, natural_gas_line
utilities_fuel **Description:** POL fuel distribution system **Feature classes:** fuel_anode_point, fuel_farm_point, fuel_hydrant_point, fuel_junction_point, fuel_pump_point, fuel_regulator_reducer_point, fuel_source_point, fuel_tank_point, fuel_valve_point, fuel_line, fuel_farm_area, fuel_junction_area, fuel_tank_area	**utilities_hcs** **Description:** heating and cooling system (small number of buildings) **Feature classes:** heat_cool_junction_point, heat_cool_pump_point, heat_cool_valve_point, heat_cool_line, heat_cool_junction_area, heate_cool, plant_area
utilities_water **Description:** water distribution system; includes both hydrant water and potable water **Feature classes:** drinking_water_sample_point, water_anode_test_station_point, water_fire_connection_point, water_fitting_point, water_hydrant_point, water_meter_point, water_pump_point, water_pump_station_point, water_rectifier_point, water_regulator_reducer_point, water_tank_point, water_valve_point, water_line, water_pump_station_area, water_tank_area	**utilities_electric** **Description:** electric distribution system **Feature classes:** elect_transformer_bank_point, electrical_capacitor_point, electrical_junction_point, electrical_meter_point, electrical_riser_point, electrical_switch_point, exterior_lighting_point, electrical_cable_line, electrical_junction_area

Figure C1. Imported feature datasets and classes.

For each dataset, conduct a first round of “cleaning”:

Step 1. Remove “abandoned” and other lines not in use.

Step 2. Make topological connections.

Step 3. Determine building adjacencies.

In this initial run with infrastructure data, a better understanding of a polyline emerges. The polyline data structure within ArcGIS allows for a group of line segments to be stored as a single feature. In other words, a polyline represents multiple line segments as a single line. An interesting question is raised: what if it were possible to model each polyline with similar attributes as a single node with facilities attached to this polyline as adjacencies? Some fidelity in the modeling process would be lost (i.e., a "chunk" of the network would be modeled as a single node), but in areas where a lot of congestion exists, this modeling method might increase performance of the model. This method might also be helpful as the polyline may have a unique "date acquired" attribute associated with it and this attribute would help in modeling the facility decay for that segment of lines.

C.2 Refinement of the Import and Topological Cleaning Procedures

(11 June 2013) This section presents a more detailed and refined procedure for importing and further topological cleaning of the data. There are four major steps in the process:

Step 1. Import the facilities feature class and the infrastructure feature class of interest. These two feature classes are the basis of the data for the simulation.

Step 2. Isolate the infrastructure lines and delete the unwanted lines. For the heating and cooling infrastructure, delete any line labeled as a "return line" and any line labeled as "abandoned". The interest is solely in whether or not a facility is connected to the infrastructure and return lines and abandoned lines provide unnecessary information.

Step 3. Ensure the topology of the network is established. There are three things to check:

Step 3(a). Ensure that lines are co-incident. Co-incidence is where the snapping functionality of ArcGIS's editing environment is helpful. Any lines that are not co-incident must be edited to be so.

Step 3(b). Ensure that lines are drawn such that their directionality makes intuitive sense. Although ArcGIS has a number of tools that might be helpful, manually adjusting the lines will be the only way to correct this aspect of the network topology. One tool that is not immediately useful is the "Flip Lines" tool available as a standard ArcGIS toolbox. Its utility is limited because it changes the directionality of an entire feature class rather than one line at a time. Another tool that is not useful is the "Display Arrows" tool in the Flow Analysis feature of the Geometric Networks add-in. As discovered earlier in the research, although the geometric networks function can simulate the flow direction, the structure of the Python code is such that the *Xto*, *Yto*, *Xfrom*, and *Yfrom* attributes of the network polylines must be set beforehand. This leads to the requirement to adjust these lines manually. In order to make the adjustments manually, each vertex in the polyline must be edited in the editing environment.

Step 3(c). Finally, ensure that each line starts and stops at building centroids. All lines did not stop at the centroids and so the feature to point tool was used to create these centroids. The steps to do so are below:

Feature to Point: → Arc Toolbox → Data Management Tools → Features→ Feature to Point

Step 4. Not all facilities will participate in a given infrastructure. Therefore, to reduce computer processor workload, reduce the facility list to only the subset of participating facilities. This requires creating a new, smaller feature class. The steps to do so are below:

Step 4(a). Select the desired facilities.

Step 4(b) Export the selection to an output table. This is done through the attributes table frame.

Step 4(c) In the ArcCatalog window, create a feature class from this new table

Step 4(d) Select "From XY table"

Step 4(e) Specify the X fields and the Y fields … this ensures the coordinates get transferred over

Step 4(f) Select "OK"

After completion of the above steps, a question concerning *topology versus data accuracy* can be raised. One of the problems encountered is the need to adjust and clean the dataset in order for the coding script to work. In order to be able to mathematically represent the network structure, topological connections must be made within the GIS data. The "before" and "after" screenshots in Figure C2 illustrate the issue.

Figure C2. Before and after screenshots for topological connections.

Note how the line in the center of the left frame is moved in order to make the connection to the building (right frame). If the distance of the line is an important factor, then this adjustment might have a significant impact on the modeling results. Currently, ensuring this topological connection (and thus being able to express it mathematically) is more important and the reason for the adjustment.

C.3 firstPoint, lastPoint Methods and the read_shp Function

C.3.1 firstPoint, lastPoint Methods

(13 Jun 2013) The *firstPoint* and *lastPoint* methods are particularly useful tools in extracting the first point and last point of a polyline. These points allow for the determination of the line directionality, which is important in the building of the directional adjacency matrix for the input-output inoperability model. Additionally, knowing the endpoints of a polyline allows for easy scanning across the network to determine a line start or end and determine if these points are inside of a facility polygon. A third method, the *within* method, can be used for this comparison. If an endpoint is

within a polygon, then the polygon label and the endpoint coordinates are stored in a dictionary for labeling. The code for this functionality is below:

```
rows = arcpy.SearchCursor(Network_Lines)
    nodes_dict = {}
    for row in rows:
        d = {}
        line_feat = row.getValue('Shape')
        firstpoint = line_feat.firstPoint
        lastpoint = line_feat.lastPoint
        facs = arcpy.SearchCursor(Facilities_FeatClass)
        for fac in facs:
            facility = fac.getValue('Shape')
            firstpoint_within = firstpoint.within(facility)
            lastpoint_within = lastpoint.within(facility)
            if firstpoint_within == True:
                d = {str(fac.STRUCTNAME + '_' +
                        str(fac.OBJECTID)):
                        tuple((firstpoint.X, firstpoint.Y))}
             if lastpoint_within == True:
                  d = {str(fac.STRUCTNAME + '_' +
                        str(fac.OBJECTID)):
                        tuple((firstpoint.X, firstpoint.Y))}
```

With this code, the coordinates for the endpoints of the network that originate or terminate within a facility can be recorded. What is left to determine are the endpoints and the directionality of those endpoints that do not terminate within a facility. Generically, within ArcGIS, these points are called “junctions”.

C.3.2 The Problem with the ready_shp Funciton.

The second portion of this entry provides some thoughts on the *read_shp* function. The *read_shp* function originally offered a promising method for determining network topology, but it was discovered that this function has a flaw. In previous work, NetworkX's *read_shp* function was used in order to extract an adjacency list for a sample networked system. Although these test runs led to successfully extracting an adjacency list, the *read_shp* function will ultimately not meet the current research needs. There are two primary reasons for this.

First, the *read_shp* function requires the underlying polyline feature class of the relevant network be in the form of a shapefile. A shapefile is a data file format unique to the ArcGIS platform and requires the creation of a separate file from the original data which introduces the problem of data integrity. If edits to the underlying polyline feature class are required (even a small spatial adjustment), the two files, the feature class and shapefile, would no longer match and any functions extracting information from the shapefile will extract outdated information. Thus, one problem is solved by abandoning the *read_shp* function.

Second, the *read_shp* function only indicates an adjacency at the start and endpoints of the polyline. Therefore, if a line originates from the middle of a second line, ArcGIS will visually depict an intersection at that junction, but the NetworkX *read_shp* function will not record an adjacency between these two lines. A possible solution to this particular problem would be to employ the *touches* method. In the data preparation phase, spatial adjustments to the utility network are necessary and these adjustments offer the opportunity to ensure proper directionality of each polyline in the network. Using the *touches* method (and the newly discovered *firstPoint* and *lastPoint* methods), a script might be possibly written which could account for each junction from the polyline feature class and ensures that the proper adjacency within the shapefile is captured. However, this solution has not been employed to date and will require additional work to test and implement the procedure.

C.4 Geometries and the "Within" and "Touches" Relationships

(18 June 2013) To date, code has been developed which uses a nested looping structure to determine the network adjacencies for each node in the system. In short, the code uses two loops that compare individual polylines of the network to each other. The outer loop iterates through the list of network polylines and for each line, an inner loop iterates through the same list in order to make a comparison. If two lines touch, another comparison is made to determine the directionality of the connection.

There are five cases of relationships that are necessary to identify. These five cases can be segregated in to two categories: within and touches. The definition of two geometries touching requires that (1) there be an intersection between the two objects and (2) this intersection does not involve the interior portions of both objects. Therefore, there can be a touching relationship when two endpoints touch (touches) or when an endpoint touches the interior of an object (within). If a touching relationship is determined, then the nature of the relationship (one of the five cases) must be determined. The five cases, divided among the two categories, within and touches, are shown below:

C.4.1 "Within" Relationships.

A "within" relationship exists when the endpoint of one line is coincident with an interior point of the touching line. This category is the simplest of the two types and two cases are illustrated in Figure C.3. Depending on which endpoint touches the polyline (firstPoint or lastPoint), the adjacency of line *a* to *b* (lastPoint of *a* is within *b*) or *b* to *a* (firstPoint of *a* is within *b*) is captured and recorded.

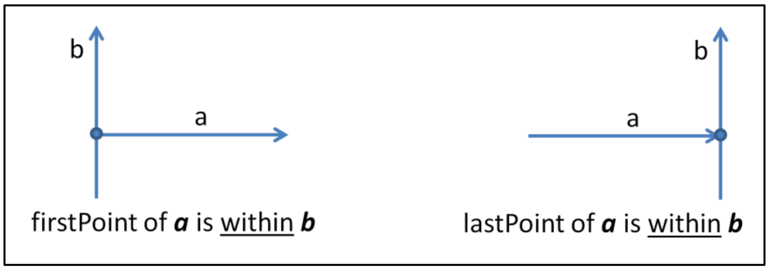

Figure C3. Two examples of a "within" relationship.

C.4.2 "Touches" Relationships.

The second set of cases is slightly more complex and encompasses the remaining three kinds of touching relationships. These cases are called "touches" because only the endpoints of both polylines touch and the interior of either polyline is not involved in the relationship. The three cases are illustrated in Figure C4.

The first case in Figure C4 shows the possibility of identifying source nodes. For now, these types of relationships should be ignored and can be later identified when facility information is introduced. The rationale behind ignoring has to do with the case when three lines form a "T" intersection. If one line ends at the intersection and two lines originate from it, the code as written would identify the two lines touching at their firstPoints as a source node, when in fact, two directional adjacencies should instead be captured.

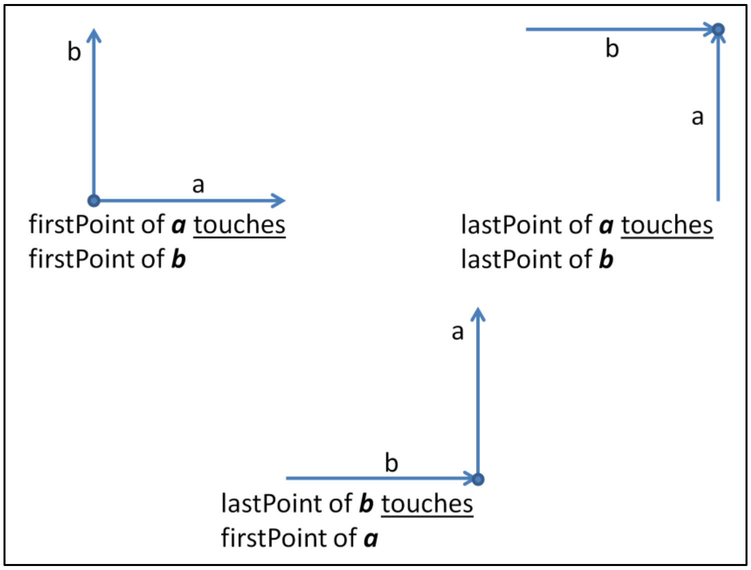

Figure C4. Three examples of a touches relationship.

The second case in Figure C4 identifies the possibility of a sink node. As with the source nodes, these relationships should also be ignored for now. Although the current network does not identify any sorts of these relationships, the possibility of errors being created at "T" intersections exists and therefore, this relationship should be ignored.

Finally, there are lastPoint to firstPoint relationships that are captured and should not be ignored. This third case is where one polyline ends where another polyline begins. Therefore, if two lines touch, and they touch in such a way that the lastPoint of one line is coincident with the firstPoint of another line, then there is a beginning to end relationship and the directional adjacency is such that it is *b* to *a*.

However, these relationships present a problem in the duplicate identification of adjacencies. Because the code is run with an embedded loop structure, two lines are compared at two distinct times. Therefore, the code captures a single adjacency between lines *a* and *b* not once, but twice. This isn't the case for the within class of relationships because the relationship is non-reversible. That is, if an endpoint of *a* is within the polyline *b*, the reverse relationship does not hold true (there is no such thing as the polyline of *b* being within the endpoint of *a*). The adjacency at endpoints is duplicated because the relationships are reversible: an endpoint in polyline *a* touching an endpoint in polyline *b* will be recorded a second time because it is the same as an endpoint in polyline *b* touching an endpoint in polyline *a*.

C.5 Correcting Topologies

(1 Jul 2013) A major phase in the research concerns correcting the network topologies within the infrastructure dataset. The particular dataset was chosen because it seemed to have the best topological relations of all the data received. However, upon closer inspection, topological errors still existed necessitating corrections be made before proceeding to the analysis portion of the research. Such corrections are depicted in Figure C5.

Figure C5 shows two examples of corrections needed throughout the data. Correction #1 is an example of a missing connection between two different networks. For this example, there is no connection between the TEP 46 KV distribution lines and the second of two structures within the switching station complex. Correction #2 is an example of a missing connection within a single electrical circuit. To correct both errors, lines will have to be added to the data (or extended to complete the respective circuits).

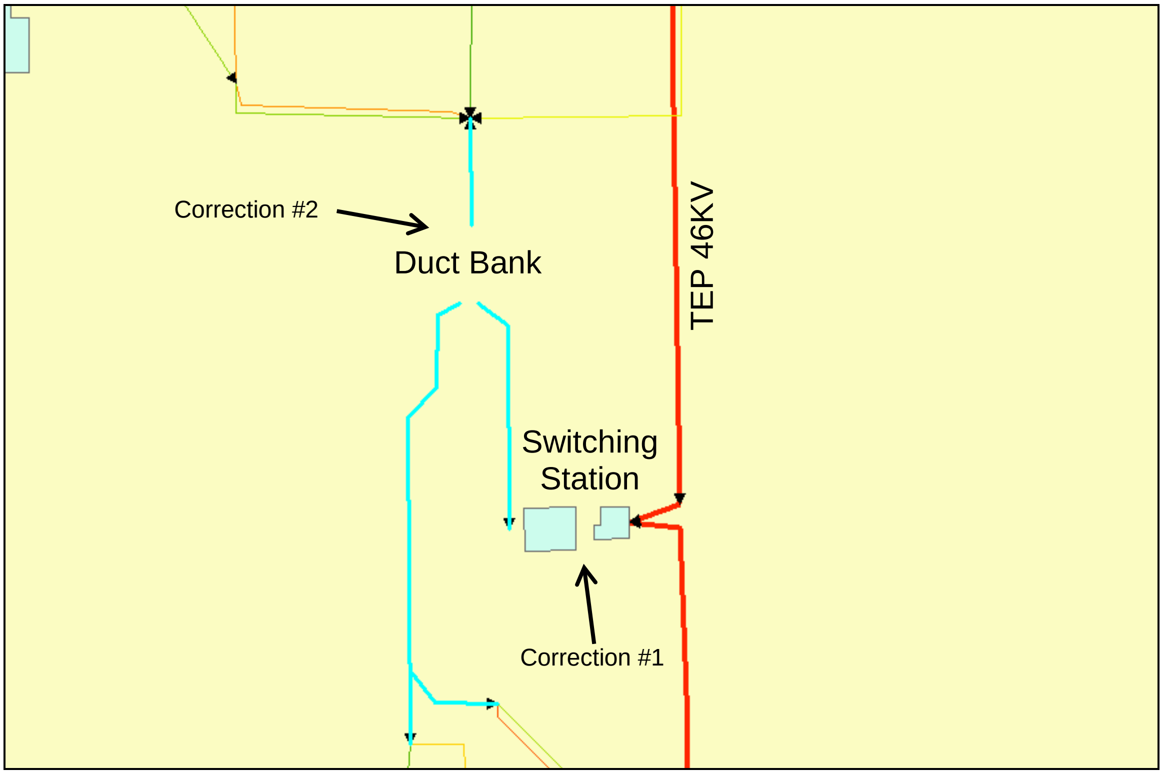

Figure C5. Examples of necessary topological corrections.

C.6 Correcting Cycles in the Water Infrastructure

(13 July 2013) Much like the electrical infrastructure, topological corrections to the dataset must be made before any analysis can take place. Figure C6 provides an output of the cycles that exist in the existing dataset. The figure displays the code for the *simple_cycles* method from the networkX module. Even after the extensive topological cleaning, the current network has twelve cycles that prevent the matrix operations in the IIM from being carried out.

```
Python Shell
File Edit Shell Debug Options Windows Help
>>> nx.simple_cycles(G)

Traceback (most recent call last):
  File "<pyshell#35>", line 1, in <module>
    nx.simple_cycles(G)
  File "C:\Python26\lib\site-packages\networkx\algorithms\cycles.py", line 191, in simple_cycles
    strongcomp = nx.strongly_connected_components(subgraph)
  File "C:\Python26\lib\site-packages\networkx\algorithms\components\strongly_connected.py", line 80,
in strongly_connected_components
    lowlink[v]=preorder[v]
KeyboardInterrupt
>>> cycles = nx.simple_cycles(G)
>>> len(cycles)
12
>>> for cycle in cycles:
        print cycle


['LINE 2430', 'LINE 2286', 'LINE 2465', 'LINE 2475', 'LINE 2183', 'LINE 2375', 'LINE 2156', 'LINE 2155
', 'LINE 2154', 'LINE 2528', 'LINE 2543', 'LINE 2431', 'LINE 2745', 'LINE 2430']
['LINE 2430', 'LINE 2286', 'LINE 2465', 'LINE 2475', 'LINE 2437', 'LINE 2606', 'LINE 2607', 'LINE 2145
', 'LINE 2908', 'LINE 2374', 'LINE 2375', 'LINE 2156', 'LINE 2155', 'LINE 2154', 'LINE 2528', 'LINE 25
43', 'LINE 2431', 'LINE 2745', 'LINE 2430']
['LINE 2430', 'LINE 2286', 'LINE 2465', 'LINE 2475', 'LINE 2437', 'LINE 2606', 'LINE 2607', 'LINE 2145
', 'LINE 2908', 'LINE 2374', 'LINE 2183', 'LINE 2375', 'LINE 2156', 'LINE 2155', 'LINE 2154', 'LINE 25
28', 'LINE 2543', 'LINE 2431', 'LINE 2745', 'LINE 2430']
['LINE 2437', 'LINE 2606', 'LINE 2607', 'LINE 2145', 'LINE 2908', 'LINE 2374', 'LINE 2375', 'LINE 2156
', 'LINE 2153', 'LINE 2465', 'LINE 2475', 'LINE 2437']
['LINE 2437', 'LINE 2606', 'LINE 2607', 'LINE 2145', 'LINE 2908', 'LINE 2374', 'LINE 2183', 'LINE 2375
', 'LINE 2156', 'LINE 2153', 'LINE 2465', 'LINE 2475', 'LINE 2437']
['WATER_TANK_3_1708', 'LINE 1598', 'WTR PMP STA_613', 'LINE 1600', 'WATER_TANK_3_1708']
['LINE 2156', 'LINE 2153', 'LINE 2465', 'LINE 2475', 'LINE 2183', 'LINE 2375', 'LINE 2156']
['WTR PMP STA_613', 'LINE 375', 'LINE 374', 'LINE 2292', 'LINE 2681', 'LINE 2675', 'LINE 2679', 'LINE
2677', 'WTR PMP STA_613']
['WTR PMP STA_613', 'LINE 375', 'LINE 2685', 'LINE 2681', 'LINE 2675', 'LINE 2679', 'LINE 2677', 'WTR
PMP STA_613']
['LINE 2498', 'LINE 2502', 'LINE 2511', 'LINE 2499', 'LINE 2498']
['LINE 2616', 'LINE 2575', 'LINE 2576', 'LINE 2572', 'LINE 2573', 'LINE 2616']
['LINE 2992', 'LINE 2995', 'LINE 2992']
>>>
Ln: 5117 Col: 155
```

Figure C6. Output for cycle detection procedure.

Each bracketed line in Figure C6 is a list of nodes that compose each of the twelve cycles in the system. On further investigation, Figure C7 illustrates the difficulty in detecting cycles visually. The primary difficulty in visual detection is due to the large volume of lines that might constitute a cycle. Figure C7 displays one cycle that has been captured at a particular "zoom" level, but other cycles exist which span larger geographic areas and others that are "hidden" within other network lines. Additionally, because the topology of the given network is not exact (i.e., preceding line end points do not match up perfectly to successive line start points), the cycle depicted in C7 shows lines that may not appear to participate in a cycle, but enhanced zooming into a particular connection shows that, in fact, it does.

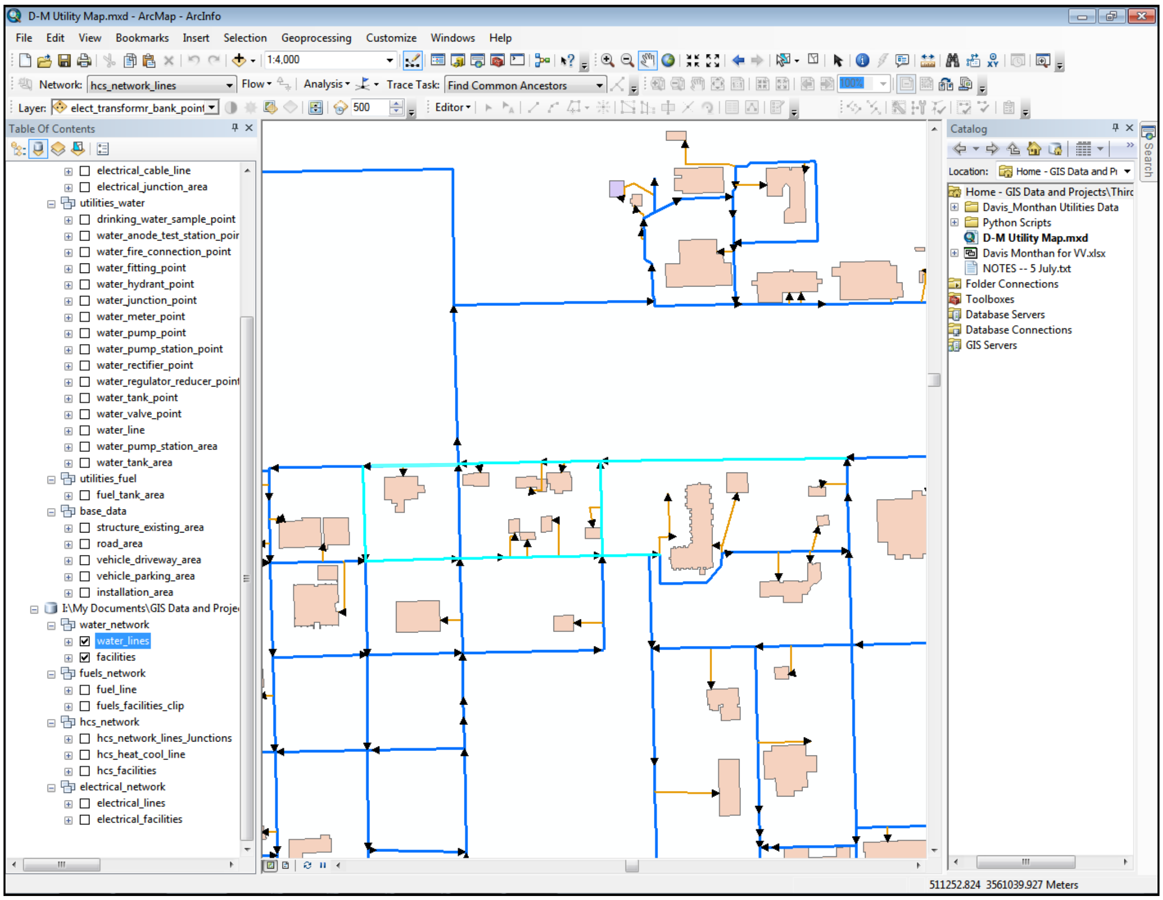

Figure C7. An example of a “cycle” in ArcMap.

C.7 Conclusion

This appendix provides a sample of the procedure logs that directly related to the topological cleaning phase of the research. The time span of the work encompassed approximately five weeks of work and focused only on the data preparation to correct the network topologies of each of the infrastructure. Without a corrected topology, analysis on the data is not possible and this cleaning phase implemented several methods to correct topologies throughout the network. These methods included manual data preparation, script development to partially automate the workflow, and script development to detect and correct cycles within the network. Further work beyond this phase includes Python script development to implement the enhanced IIM model as well as script development for plotting and display of the results.

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Vita

Major Vhance V. Valencia grew up in a military home and continues to follow in his father's footsteps with his own service in the United States Air Force. Privileged to travel the world as a military dependent, he graduated from San Diego State University in San Diego, California with a Bachelor of Science degree in Mechanical Engineering. Shortly thereafter, Maj Valencia entered the United States Air Force with an officer commission through the university's Air Force Reserve Officer Training Corps, Detachment 075. Since then, he has held a number of positions as an Air Force civil engineer with progressive leadership and engineering responsibility.

Some of Major Valencia's assignments include serving as the engineering flight commander for the 379th Expeditionary Civil Engineer Squadron at al Udeid Air Base, Qatar and construction program manager for the Air Force Civil Engineer Center at Ramstein Air Base, Germany. In both positions, he oversaw and directed the construction of facility and infrastructure systems supporting U.S. military forces stationed throughout the Middle East and Europe. The challenges encountered in these assignments spurred his interest in the management and maintenance of infrastructure systems. Other assignments include infrastructure requirements identification and planning at Langley Air Force Base, Virginia and directing the responsible exit of a major Air Force construction office from Baghdad, Iraq. Major Valencia was previously assigned to the Air Force Institute of Technology (AFIT) where he earned a Master of Science degree in Engineering Management and studied the personal attributes of construction project managers as part of his master's thesis requirement. Major Valencia is a licensed Professional Engineer and, upon graduation, he will serve as faculty in AFIT's Department of Systems and Engineering Management leading the instruction of the Master's of Engineering Management program for the Air Force civil engineer career field.

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14. ABSTRACT
As modern infrastructures become more interconnected, the decision-making process becomes more difficult because of the increased complexity resulting from infrastructure interdependencies. Simulation and network modeling provide a way to understand system behavior as a result of interdependencies. One area within the asset management literature that is not well covered is infrastructure system decay and risks associated with that decay.

This research presents an enhanced version of Haimes' input-output inoperability model (IIM) in the analysis of built infrastructure systems. Previous applications of the IIM characterized infrastructure at the national level utilizing large economic databases. This study develops a three-phased approach that takes component level data stored within geographic information systems (GIS) to provide a metric for network interdependency across a municipal level infrastructure. A multi-layered approach is proposed which leverages the layered data structure of GIS. Furthermore, Monte Carlo simulation using stochastic decay estimates shows how infrastructure risk as a result of interdependency effects changes over time. Such an analysis provides insight to infrastructure asset managers on the impact of policy and strategy decision-making regarding the maintenance and management of their infrastructure systems.

15. SUBJECT TERMS
Infrastructure, interdependency, networks, asset management, risk

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