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A COMPUTATIONAL FRAMEWORK FOR OPTIMIZATION-BASED INTERDEPENDENT INFRASTRUCTURE ANALYSIS AND VULNERABILITY

by

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Civilian communities and military installations operate numerous critical infrastructure systems to deliver services like power, water, mobility, and communications to people and missions. The vulnerability of these systems can be measured by considering the robustness of each infrastructure network on its own or by considering the interdependencies between different networks. Diverse infrastructure network models are available to analyze system vulnerability, yet a standard architecture for linking pre-existing models for interdependent analysis does not exist. We develop a computational framework to generate combined models that link multiple network-flow optimization models together for interdependent analysis. We validate our methods and implementation in the Python programming language with well-studied interdependent energy networks. We further demonstrate the versatility of our methods by developing a new assessment of fictitious energy and transportation networks with models not originally created with interdependencies. Overall, this work develops a standard way to conduct interdependent infrastructure analysis with pre-built models and sets a foundation for future analysis of other interdependencies and systems.

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ABSTRACT

Civilian communities and military installations operate numerous critical infrastructure systems to deliver services like power, water, mobility, and communications to people and missions. The vulnerability of these systems can be measured by considering the robustness of each infrastructure network on its own or by considering the interdependencies between different networks. Diverse infrastructure network models are available to analyze system vulnerability, yet a standard architecture for linking pre-existing models for interdependent analysis does not exist. We develop a computational framework to generate combined models that link multiple network-flow optimization models together for interdependent analysis. We validate our methods and implementation in the Python programming language with well-studied interdependent energy networks. We further demonstrate the versatility of our methods by developing a new assessment of fictitious energy and transportation networks with models not originally created with interdependencies. Overall, this work develops a standard way to conduct interdependent infrastructure analysis with pre-built models and sets a foundation for future analysis of other interdependencies and systems.

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List of Acronyms and Abbreviations

ABM Agent-Based Modeling

ACOPF Alternate Current Optimal Power Flow

AD Attacker-Defender

AMPL A Mathematical Programming Language

bbl Barrel

CAS Complex Adaptive Systems

CID Naval Postgraduate School Center for Infrastructure Defense

CIS critical infrastructure systems

CPS cyber–physical–social

CRISIS Civil Restoration with Interdependent Social Infrastructure Systems

DAD Defender-Attacker-Defender

DCOPF Direct Current Optimal Power Flow

DIS Distributed Interactive Simulation

DM dependent model

DoD Department of Defense

EGRET Electrical Grid Research and Engineering Tools

GAMS General Algebraic Modeling System

GE General Electric Company

HLA High Level Architecture

ILN	interdependent layer network
IMN	interdependent multi-layered network flow
INCORE	Interdependent Networked Community Resilience Modeling Environment
ISP	Internet Service Provider
KW	kilowatt
KWh	kilowatt-hour
MASINT	measurement and signature intelligence
MDI	Mission Dependency Index
MIP	mixed-integer programing
MW	megawatt
MWh	megawatt-hour
MPH	miles per hour
NATO	North Atlantic Treaty Organization
NIST	National Institute of Standards and Technology
NPS	Naval Postgraduate School
OOM	Object-Oriented Modeling
PCCIP	U.S. President's Commission on Critical Infrastructure Protection
PDD	pressure dependent demand
PPD	Presidential Policy Directive
PSLF	Positive Sequence Load Flow
PySP	Pyomo Stochastic Programming
SCADA	supervisory control and data acquisition

SM serving model

SRWBR short range wide band radio

TCP Transmission Control Protocol

UDP User Datagram Protocol

UICAP Utility Infrastructure Condition Assessment Program

UIS urban infrastructure systems

USG United States government

USN U.S. Navy

USVI U.S. Virgin Islands

VPH vehicles per hour

WDN Water Distribution Network

WNTR Water Network Tool for Resilience

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Executive Summary

Critical infrastructure systems (CIS) are the foundation of modern society. CIS provide services like electric power, clean water, mobility, communications, and fuel. Without these services, modern society would experience significant impacts to the economy and safety, and infrastructure operations and maintenance to keep these systems in good working condition is crucial for day-to-day life. Understanding their vulnerabilities and responses to large-scale, rare, unexpected, or unknown failures is also essential to invest in projects with the highest benefit for society. A key recognition is that CIS are also interdependent on each other (e.g., water systems need electricity to function and power systems need water to function), such that the vulnerability of one system can affect the operations of another, and vice versa. Analysis of these interdependencies and their implications for system protection and resilience is an important area of research.

This thesis focuses on developing standardized methods and tools that enable the modeling of interdependent CIS and assess their vulnerabilities. We focus our work on island and military installation CIS because they share a number of important features that make them useful for developing interdependency analysis methods. For example, many of these systems are at a local or community scale, have clear geographic and physical boundaries, and distinct ownership and operational boundaries.

We review the literature on CIS modeling and vulnerability analysis to inform a generic framework for studying interdependent systems. CIS almost always have a network structure, and their function is often modeled as a network flow problem. Whereas network optimization methods are widely used and pre-existing models exist, there are far fewer studies considering their interdependencies. The construction and optimization of interdependent models is not trivial, and is often completed by creating an entirely new model with interdependencies built in. However, we do not find a standard model formulation or implementation that considers the connection of pre-existing infrastructure models for interdependent analysis.

We build upon recent work on interdependent multilayer network flow problems to develop a framework for combining pre-existing models. Our resulting framework generates

network optimization models we call *combo-models* that link two networks together for interdependent analysis. We implement our framework using Pyomo optimization model objects and a generator function that takes user input for combo-model construction. This results in an easy way to link pre-built network flow models together for interdependent analysis.

We validate our methods with interdependent energy network models. We implement fuel and electric power network flow models in Pyomo based on past studies. However, past studies included model elements for interdependent analysis in initial model formulation. Here, we develop the fuel and electric power networks as standalone Pyomo model objects, then use our combo-model generator function to add in necessary model elements. We validate this new approach with simple and realistic energy networks. Results show the combo-model methods enable interdependent vulnerability analysis and can reproduce results from past studies.

Then, we develop a novel analysis of interdependent energy and transportation systems. We implement a pre-existing transportation model that was not created for interdependent infrastructure analysis. We use our combo-model methods to link it to fuel and electric power models. We analyze the interdependent function of energy and transportation systems with simple and realistic networks developed for islands in the U.S. Virgin Islands. While models are fictitious, they show the versatility of the combo-model methods for generating interdependent infrastructure models and demonstrate the importance of considering interdependencies in vulnerability assessment of islands and installations.

Our methods and analyses provide a foundation for future CIS vulnerability research. The majority of analyses of interdependencies study at most two systems, where combo-model methods support analyzing a larger number of networks. Methods support federating optimization models with other operator models, such as simulation models for water systems. Finally, our methods focus on the physical interdependencies, where future work can incorporate others (e.g., geographic co-location). Taken together, future analyses on real systems using the combo-model methods enable new insight into CIS protection and resilience.

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CHAPTER 1:
Introduction

The life and welfare of modern society relies on critical infrastructure systems (CIS) to provide services like electrical power, clean water, mobility, communications, and fuel. Infrastructure operations and maintenance to keep these systems in good working condition is crucial for day-to-day life. Understanding their vulnerabilities and responses to large-scale, rare, unexpected, or unknown failures is also essential to invest in projects with the highest benefit for society. A key recognition is that CIS are also dependent and interdependent on each other (e.g., water systems need electricity to function and electric power systems need water to function), such that the vulnerability of one system can affect the operations of another, and vice versa. Analysis of these interdependencies and their implications for system protection and resilience is an important area of research that supports safety and security. This thesis focuses on developing standardized methods and tools that enable the modeling of interdependent CIS and assess their vulnerabilities.

1.1 Critical Infrastructure Systems

The most important infrastructures for a functioning society are dubbed "critical" infrastructure. What constitutes critical infrastructure depends on definitions found in guiding legislation, such as the definition used in the United States of America found in the U.S. Patriot Act of 2001, where critical infrastructure is defined as: "(...) systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters" (United States of America 2001).

This definition emphasizes that the failure of a CIS — or worse, many of them — can have a huge impact on health, security and safety of the affected area and communities. Thus, it is the policy of the United States to ensure "that any physical or virtual disruption of the operation of the critical infrastructures of the United States be rare, brief, geographically limited in effect, manageable, and minimally detrimental to the economy, human and government services, and national security of the United States" (United States of America 2001).

This policy was made practical in 2013 by Presidential Policy Directive (PPD) 21, *Critical Infrastructure Security and Resilience*, which directed the U.S. federal government to "strengthen the security and resilience of its critical infrastructure against both physical and cyber threats" (The White House 2013). The goal of PPD-21 was to improve the resilience of CIS and attenuate potential impacts on "national security, economic stability, public health and safety, or any combination thereof" (The White House 2013). Here, PPD-21 defines resilience as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" (The White House 2013).

PPD-21 further delineates the sectors and systems that constitute CIS. The *most* critical of these systems outlined in PPD-21 were energy and telecommunication systems because of their enabling function for other critical infrastructures (The White House 2013). In addition, the following 16 critical infrastructure sectors are identified in PPD-21 and are currently the focus of federal efforts to improve CIS resilience:

- Chemical
- Commercial Facilities
- Communications
- Critical Manufacturing
- Dams
- Defense Industrial Base
- Emergency Services
- Energy
- Financial Services
- Food and Agriculture
- Government Facilities
- Healthcare and Public Health
- Information Technology
- Nuclear
- Transportation
- Water and Wastewater (The White House 2013)

Not only is the U.S. focusing on protecting CIS, but so are many other countries, unions and alliances. For example, the European Union provides its own definition of critical infrastructure that guides European protection and resilience activities: "'critical infrastructure' means an asset, system or part thereof located in Member States which is essential for the maintenance of vital societal functions, health, safety, security, economic or social well-being of people, and the disruption or destruction of which would have a significant impact in a Member State as a result of the failure to maintain those functions" (Council of the European Union 2008).

CIS protection and resilience is also relevant in military operations, such that the North Atlantic Treaty Organization (NATO) is also focusing on CIS resilience. After the decision at the 2016 Summit of the NATO in Warsaw to seek for preparation for a full spectrum of future threats (including any form of armed attack), the members agreed on the following seven baseline requirements for national resilience (North Atlantic Treaty Organization 2020):

1. Assured continuity of government and critical government services: for instance the ability to make decisions, communicate them and enforce them in a crisis;
2. Resilient energy supplies: back-up plans and power grids, internally and across borders;
3. Ability to deal effectively with uncontrolled movement of people, and to de-conflict these movements from NATO military deployments;
4. Resilient food and water resources: ensuring these supplies are safe from disruption or sabotage;
5. Ability to deal with mass casualties: ensuring that civilian health systems can cope and that sufficient medical supplies are stocked and secure;
6. Resilient civil communications systems: ensuring that telecommunications and cyber networks function even under crisis conditions, with sufficient back-up capacity. This requirement was updated in November 2019 by NATO Defence Ministers, who stressed the need for reliable communications systems including 5G, robust options to restore these systems, priority access to national authorities in times of crisis, and the thorough assessments of all risks to communications systems; and,
7. Resilient transport systems: ensuring that NATO forces can move across Alliance territory rapidly and that civilian services can rely on transportation networks, even

in a crisis (North Atlantic Treaty Organization 2020).

Overall, CIS resilience is a priority for numerous countries, unions, and alliances. The specific justifications and systems that comprise CIS may differ, but their intent and application are very similar and well-integrated. Importantly, each country, union, and alliance focuses on identifying vulnerabilities within and across systems to develop effective resilience strategies.

1.2 Critical Infrastructure Vulnerability

Decisions to protect CIS and improve their resilience rely on technical methods for assessing CIS vulnerability. Interruptions in critical services occur for many reasons, such as natural hazards, resource unavailability, hostile or terrorist attacks, and technology failures. These stressful events on their own may not disrupt services, but rather the failure of infrastructure as a result from these events do. Thus, it is important to identify the likelihood and consequences of infrastructure losses before they occur. The goal of CIS vulnerability assessment is to use different perspectives on event likelihood and consequences to determine the assets or sub-systems, that, if failed, lead to the greatest impacts on society.

CIS vulnerabilities originate from many different sources. For example, poorly operated, and maintained infrastructure is vulnerable because it is unreliable and likely to fail during a stressful event (or even during normal operations) (Zio 2016). Infrastructure that is in high-risk locations that experience frequent disasters and attacks are also vulnerable because they are the more likely to experience stressful events (Haimes 2006; Aven 2011). Systems with poor designs that are easily exploited or have single points of failure are vulnerable, especially if targeted by adversaries (Alderson et al. 2014). And systems with ineffective decision-support tools to sense, anticipate, adapt, and learn (Park et al. 2013; Thomas et al. 2019) from surprises are vulnerable to surprising events that challenge normal operations (Eisenberg et al. 2019).

In all cases, CIS are commonly found to be unreliable, risky, easily targeted, surprised, or otherwise vulnerable when they have underappreciated interdependencies with other infrastructure systems (Clark et al. 2019). Dependencies or interdependencies between different CIS (e.g., electric power and water) make a failure in one system affect another, and vice versa. Importantly, interdependencies can lead to cascading failures, where initial losses in one system cascade to affect the operations of another. An example of such a dependency or interdependency is a power outage in a electric power network, which leads to an outage of a water pump in a water distribution network. Cascades can also affect the original infrastructure system exacerbating previous service losses, such as if the water pump that failed in the previous example was used for cooling power generation plants. Here a power failure can cascade through the water system to create a larger power interruption.

Interdependencies influence vulnerability and can impact service provision at all scales of CIS operations (e.g., national, regional, and local). This thesis is specifically motivated by examples of interdependencies that affect civilian and military CIS at the community, island, and military installation scale.

1.2.1 Island and Military Installations Systems

CIS vulnerability and resilience analysis at the local scale is crucial for advancing knowledge of interdependencies and their effects. Many CIS across the U.S. are regional in operation and management, such that source of vulnerabilities are difficult to pinpoint due to the numerous owners, operators, and interconnected assets that must be considered in analysis (Alderson 2019). Here, the implications of a single dependency or interdependency across systems may be difficult to quantify. Analysis of local CIS systems at the community scale is more straightforward and the effects of interdependencies across systems can be explicitly modeled and quantified.

Island and military installation CIS share a number of important features that make them particularly useful for developing interdependency analysis methods and tools. First, many island systems are at a local or community scale, simplifying analysis. Island and installations also have clear geographic and physical boundaries that isolate them from nearby or regional CIS, such as isolated locations or a "fenceline" separating civilian and military systems. These geographic and physical boundaries exist both within the continental U.S. and in more remote environments like island territories and military outposts. Related to physical borders are distinct ownership and operational boundaries as island and installation systems tends to be managed separately from larger regional systems. This reduces analysis complexity by only involving decision-making by one or few entities. Finally, island and installation systems often have more stringent constraints, such that there is limited physical space, funding, or otherwise limits on the size and complexity of the systems and what they can manage.

Examples of island systems motivating this work are the lifeline infrastructures in the U.S. Virgin Islands (USVI). In 2017, two Category-5 hurricanes (Irma and Maria) made indirect hits on the USVI territory within a two-week period. Since these events, there has been significant work to assess the vulnerability and resilience of island electricity (Bunn 2018; Wille 2019), water (Wille 2019; Borgdorff 2020), transportation (Good 2019; Routley 2020; Bengigi 2020), and telecommunications systems (Wine 2020; Moeller 2020). Vulnerabilities of individual systems in the USVI are exacerbated by interdependencies. For example, loss of electricity can cause water and internet outages and failure of power poles can block roadways (Good 2019). Loss of internet and wireless communications impacts recovery operations across all systems as many USVI operators use cell phones for coordinating recovery (Wine 2020). Failures in water systems can lead to flooded and destroyed roads impeding some communities from accessing disaster supplies (Routley 2020). And failures in transportation systems slows down the recovery of all USVI CIS by reducing the mobility of recovery crews and equipment (Bengigi 2020).

Examples of installation systems motivating this work are the CIS that support mission essential functions across military services and have experienced recent, major disasters. For example, Marine Corps Base Camp Lejeune in North Carolina, that was hit by Hurricane Florence in September 2018 which disrupted installation CIS and mission essential operations (Klare 2019). In particular, the methods developed in this thesis are meant to support resilience requirements set by the U.S. Department of Defense (DoD) for military installations in response to these disaster events. Resilience requirements within the DoD vary by branch and related critical service needs:

- **U.S. Navy:** The Navy requires electric energy supply for 7 days after being disconnected from the public grid or not delivered by it. This is being accomplished mostly by local fuel powered generators at important parts of the internal grid (e.g., hospitals, command and control facilities, or dining facilities) (Navy Facilities Engineer Command 2017).
- **U.S. Air Force:** The Air Force also requires 7 days of guaranteed energy supply for critical infrastructures on their bases or for the time needed to relocate a mission if it

takes longer (Secretary of the Air Force 2020).

- **U.S. Army:** To ensure mission-essential functions for supporting critical missions, the Army is requiring continuous water and electric power supply for at least 14 days (Secretary of the Army 2017).
- **U.S. Marine Corps:** The Marine Corps follows the same requirements as the U.S. Navy for energy resilience. However, similar to the Army, the Marine Corps plans to be self-reliant on electric energy and water for a minimum of 14 days (Marine Corps Installations Command 2019). They are also considering food distribution, logistical mobility, and communications.

1.3 Operations Research Techniques for Vulnerability Analysis

CIS vulnerability analysis is supported by the three pillars of Operations Research — optimization, statistics, and stochastic processes. However, optimization models form the technical basis for the vast majority of CIS vulnerability assessments. Since CIS are almost always having a network structure, they can easily be modeled as a network flow optimization problem (Alderson et al. 2014), where the type of the problem depends on the type of the infrastructure:

- Electric power networks can be modeled as *minimum cost network flow problems*;
- Potable water distribution networks can be modeled as *maximum flow problems*;
- Transportation networks (e.g., streets and railroad networks) can be modeled as *multi-commodity flow problems*; and,
- Mobile telecommunications can be modeled as *coverage problems*.

Essentially every CIS can be represented as a network and its operations can be modeled with an appropriate optimization problem. In general, the objective function for a CIS optimization model relates to the system function. Vulnerability analysis using optimization models can be conducted by studying the system function during normal operations and measuring changes in function after the CIS is damaged (Sharkey et al. 2020). This can be done by either using network interdiction models to optimize which connection removal would have the largest impact on the model, or using exhaustive enumeration, where every possible state of a network is being modeled, run and analyzed (Alderson et al. 2015).

Here, network damage is represented by binary variables that indicate functioning and non-functioning infrastructure (Sharkey et al. 2020). Whereas exhaustive enumeration is computationally intensive and may be infeasible to complete in a reasonable time period, but is easier to model and generalize.

Instead of using binary variables for network damage, it is also possible to introduce uncertainty with stochastic interdiction, so that the damage to network components is not definite, but has a probability of failure Sharkey et al. (2020). The objective (value) of the optimization problem will then have a lower and upper bound, instead of a fixed value.

Whereas network optimization methods for CIS vulnerability analysis are widely used, there are far fewer studies considering network interdependencies with other CIS systems. For analytical purposes, it is more efficient to analyze infrastructure network vulnerability without considering interdependencies to support disaster operations. However, this does not consider connections to other infrastructures and cannot capture cascading failures that originate in one CIS and cause problems on other networks. Importantly, it is difficult to identify the operational and functional effects of interdependencies without explicitly modeling both networks and their connections. This is why interdependent models are important to gain insights in the behavior of these interconnected networks.

The construction and optimization of these interconnected models is not trivial, because of their diversity of functions and their associated optimization problems. In fact, some CIS operations and physics are so complicated that it is common practice to simulate infrastructure operations instead of optimizing them. However, simplifying too much can lead to analysis problems and an inability to properly characterize vulnerabilities.

For example, a source of problems when handling damage or disturbances of an infrastructure network can be the human-in-the-loop (Eisenberg et al. 2020). Vulnerability analysis usually assumes that the operator of a infrastructure system is totally and correctly aware of the problem and is acting accordingly. But humans usually don't act as expected. For example, sensing to be aware of and understand disaster impacts must be available to decision-makers to make "correct" decisions. The effect of correct and incorrect decision-making is not, or cannot be easily implemented, in standard CIS optimization models. Interdependencies exist here as well, such as networks interconnected with telecommunication networks and control systems (supervisory control and data acquisition (SCADA)), called cyber–physical–social (CPS) systems. Eisenberg et al. (2019) wrote about the problem of having a model as a decision support system for control personnel of CIS. The factor of being "surprised" and thus not understanding what the real kind of a problem is, can worsen a humans' reaction, because of inputting the wrong data into the decision support system, drawing wrong conclusions and then acting wrong for the system or being forced to improvise.

Overall, more research should be conducted to advance network optimization to consider interdependent effects and relate these models to network resilience. Sharkey et al. (2020) outlines four key concepts defined by (Woods 2015) of resilience that are supported by network optimization models, with an emphasis on CIS systems: robustness, rebound, extensibility, and adaptability. A better understanding of the effect of interdependencies on CIS operations and vulnerabilities supports each of these concepts and their associated resilience goals.

1.4 Thesis Goals

The goal of this thesis is to develop a standard way to consider CIS interdependencies using optimization models. In particular, we build on methods for considering interdependencies in network flow optimization and apply them to infrastructure networks. We develop a computational framework and architecture that enables the modeling of different types of infrastructure networks in a standardized way. We demonstrate our approach using established interdependent models for fuel and electric power systems and demonstrate their validity for vulnerability assessment of three or more systems with a new model of a transportation network, which was never constructed for interdependent system analysis.

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CHAPTER 2:
Literature Review

To standardize the modeling and analysis of interdependent infrastructure systems, we review which CIS interdependencies exist, how they work, and how they have been studied with models and available open source software.

2.1 Critical Infrastructure Interdependency Concepts

The relationship between interdependencies and CIS vulnerabilities was first mentioned in the report of the U.S. President's Commission on Critical Infrastructure Protection (PCCIP) in 1997 with respect to cyber dependencies (President's Commission on Critical Infrastructure Protection 1997). Based on this report, canonical research was completed by Rinaldi et al. (2001) to develop a useful taxonomy of interdependencies that has influenced the research field. Rinaldi et al. (2001) describes interdependencies across CIS in terms of shared needs. These needs are defined as *dependencies* and *interdependencies*, where dependencies are unidirectional (one system only depends on the other) and interdependencies are bidirectional (both depend on each other). Rinaldi et al. (2001) also describes CIS as Complex Adaptive Systems (CAS). This expression describes, that infrastructures and their parts can be seen as interacting entities, which are exchanging information and/or resources; and while getting and sending this goods, each infrastructure is adapting itself to its context and other infrastructures. This relates to supply and demands from dependencies and interdependencies.

Examples of interdependencies presented by Rinaldi et al. (2001) are reproduced in Figure 2.1, which shows how many interdependencies exist even with few CIS for normal operations. This number and complexity of these relationships increases with every added system.

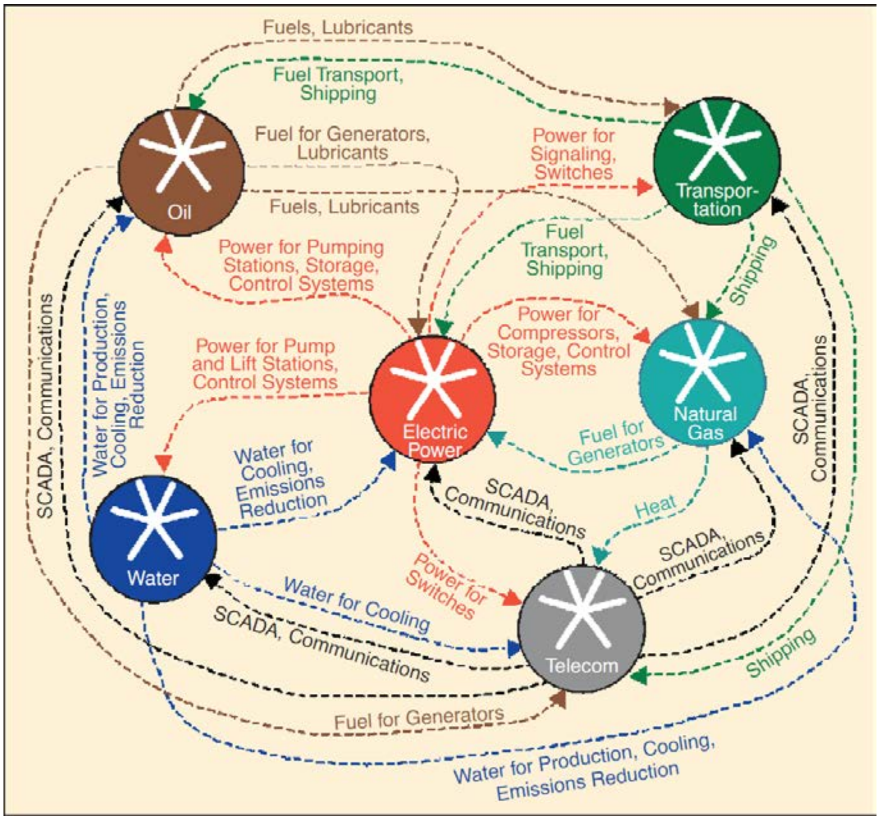

Figure 2.1. Examples of Interdependencies from Rinaldi et al. (2001). The authors show shared needs across electric power, water, oil, transportation, natural gas, and telecommunications systems. The complex relationships lead to interdependencies across different networks such that failures in one system can affect the function of another.

One of the key contributions of Rinaldi et al. (2001) was a taxonomy of different CIS interdependencies. In particular, the authors define four distinct interdependencies:

- **Physical:** when infrastructure systems are connected via supply and demand relationships to enable operations (e.g., a water-pump requiring electricity to operate);
- **Geographic:** when infrastructure are nearby each other in physical space and can be affected by the same problem (e.g., a natural disaster) due to their proximity;
- **Cyber:** when infrastructures must exchange or share information to operate (e.g., SCADA systems to manage the electric power grid); and

- **Logical:** when infrastructures have rules, decision-making, and regulatory needs that enable or inhibit collaboration and coordination (e.g., blackouts caused by ineffective fuel contracts even if the natural gas system is functioning and gas is available).

The goal of incorporating physical, geographic, cyber, and logical interdependencies in CIS vulnerability analysis is to determine how they may lead to unexpected system failures. Rinaldi et al. (2001) also defines several ways in which interdependencies lead to infrastructure failures:

- **common cause failure**, where the failure of two or more systems is caused by the same reason (e.g., earthquake, flooding, etc.);
- **cascading failure**, where the breakdown of an infrastructure system causes another one to fail (e.g., water pump not working because of a loss of electric power); and,
- **escalating failure**, where the loss of a system results in a longer recovery time of another system, both failed by different reasons (e.g., damaged road leads to an increased driving time of a repair crew for other infrastructure).

Since Rinaldi et al. (2001), several authors have made important contributions to CIS interdependency concepts. Sharkey et al. (2016) advanced interdependency concepts to consider system restoration in addition to failure. After a CIS failure, it can be difficult to restore systems because of an interdependency when trying to repair them. Sharkey et al. (2016) defined this type of interdependency, a *restoration interdependency*, as follows: "A restoration interdependency occurs when a restoration task, process, or activity in an infrastructure is impacted by a restoration task, process, or activity (or lack thereof) in a different infrastructure" (Sharkey et al. 2016, p. 1). Sharkey et al. (2016) demonstrates that restoration interdepedencies make it is very important to have effective communication between different network operators to restore interdependent services. An example for this type of interdependency would be if electric power is needed to repair a part of a water network, but the issue in the water network was caused by a power outage and the electric power is not yet restored. In general are these types of interdependencies only reveal themselves if an extreme event causes the failure of multiple infrastructure networks.

In addition to the effects of interdependencies on failures and recovery, Derrible (2017) provides an overview of how interdependencies in urban systems relate to infrastructure development practices. Interdependencies are very important when planning urban CIS because the density of infrastructure and the amount of needed supplies is higher. As older cities had a lot of time to grow from a few houses to small villages or big cities, their infrastructure is mostly interconnected with a semi-lattice structure because it grew in the same speed as the city. When planning new cities and building them up quickly, CIS tend to have a hierarchical tree structure (see Figure 2.2). Here these supply systems are called urban infrastructure systems (UIS) and Derrible (2017) emphasizes the importance of good and intensive communication and coordination between the different departments and companies, who are mostly only responsible for one UIS each.

While the semi-lattice structure is more complicated and requires more coordination, semi-lattice structures demonstrate more resilience to failures than hierarchical trees. In a semi-lattice structure, the damage of an arc has, in the best case, no influence on system function. This emphasizes decentralization for system robustness, but also emphasizes the need for to assess system function alongside interdependencies as their robustness may hide latent vulnerabilities. In contrast, hierarchical systems only require a single main arc (e.g., bottleneck) to be broken and the entire system may fail to function.

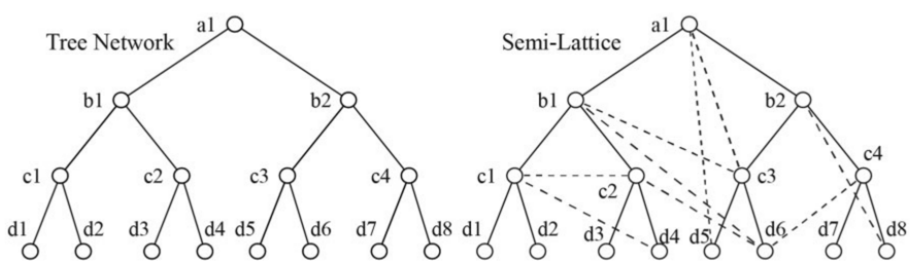

Figure 2.2. Network Representation of Tree versus Semilattice. Critical infrastructure is often planned and designed with a top-down perspective that produces systems with tree-like structure (left). Derrible (2017) argues that the dependencies between multiple systems (numbers) at different scales (letters) lead to semi-lattice interdependencies that can cause cascading and unexpected failures (right). Source: Derrible (2017).

We build on these interdependency concepts to develop models of CIS systems. In particular, we build on the taxonomy of interdependencies developed by Rinaldi et al. (2001) to guide the connection of CIS models. We relate vulnerabilities to their effects on system failure.

2.2 Modeling Interdependent Infrastructure

There is significant research motivating the need to study interdependent infrastructure systems with operations research-based approaches. We review the advantages of optimization and simulation-based methods for interdependent infrastructure modeling and described a series of infrastructure operator models useful independent and interdependent system analysis.

2.2.1 Generic Methods for Interdependent System Modeling

Ouyang (2014) provides a comprehensive review of interdependent infrastructure models and their relationship to system vulnerability and resilience. Ouyang (2014) overviews studies of interdependent systems in the following CIS sectors:

- Telecommunications
- Electric Power Systems
- Natural Gas and Oil
- Banking and Finance
- Transportation
- Water Supply Systems
- Government Services
- Emergency Services

Across the literature, Ouyang (2014) identifies different approaches for modelling interdependencies and their advantages and disadvantages. The author compares analytical approaches based on their ability to improve resilience across 16 sample strategies. Ouyang (2014) finds High Level Architecture (HLA)-based model able to support all 16 strategies because it is a hybrid approach, integrating other of interdependency analysis. Besides hybrid approaches, Ouyang (2014) finds network-flow-based methods useful for support 11 resilience strategies and simulation-based methods like Agent-Based Modeling (ABM) supporting 8 resilience strategies. Together, optimization via network flow and simulation via ABM (or otherwise) methods can yield a comprehensive approach to assessing CIS interdependencies.

Several methods discussed by and developed since the review by Ouyang (2014) are generic to support the analysis of any infrastructure system. An influential approach for modeling infrastructure interdependencies with network optimization was based on economic Leontief input-output models (Leontief 1951). Leontief modeled the required goods needed from each economic sector for a specific sector in economy to be able to maintain production.

This model was adapted to fit the interdependencies between infrastructure models, where economic sectors are replaced with infrastructure systems and the amount of production represented the system functionality. Recent advances in network flow optimization and interdependent infrastructure analysis are largely similar to this method. However, rather than treating CIS as sectors, network flow optimization explicitly models CIS components and their interactions, which is necessary to understanding vulnerability (Ouyang 2014). Here, system function is measured via optimal flows across network systems.

When using network optimization models it is not only possible to compute the optimal flow and to detect what happens during a failure scenario (e.g., a pipeline break), it is also possible to construct game theoretic and bi-level optimization to maximize network damage and identify worst-case failures. Alderson et al. (2014) describes this approach as an Attacker-Defender (AD) or Defender-Attacker-Defender (DAD) model, where AD uses a bi-level framework where worst-case attacks are represented by binary variables turning CIS components on and off. DAD is a tri-level framework that includes an initial design phase to protect networked CIS. In all cases Alderson et al. (2014) describes CIS as *operator models* since their optimization represents the worst-case or best-case operations of realistic systems. For the remainder of this work, we use this term for optimization models applied to CIS (Alderson et al. 2014).

Network optimization models are insufficient for CIS vulnerability analysis because they are not able to simulate the effects of discrete events. Instead, it is recommended to include stochastic and simulated events in optimization for performing interdependency analysis. This is possible with Object-Oriented Modeling (OOM) techniques possible in most standard programming languages (Nan and Eusgeld 2011). Developing simulations, such as an ABM where the behavior of individual objects of the model is defined and simulated over time, OOM is used to give individual model units updateable information and create a global clock for tracking system behavior and enable networked elements to communicate with each other. This technique enables time-dependent and event-driven simulations that are generally not studied with network flows. Some CIS function are normally modeled in this way because their physics are too complicated to solve with optimization. For example, hydraulic balancing is a simulation-based method that is standard to model water distribution system operation used across the potable water industry (Klise et al. 2018).

When combining multiple simulation models (hybrid approach), HLA and Distributed Interactive Simulation (DIS) are the most used frameworks. With these frameworks the connection between multiple simulations is modeled. Mostly the simulations are running parallel and exchange information and status via the framework, so that they stay synchronized.

Recent work by Enayaty Ahangar et al. (2020) recommends the use of multi-layered network flow models for analyzing interdependencies between CIS, where each infrastructure is a different network layer (or set of layers). In this approach, CIS components are represented by network nodes and arcs and flow within and among networks represents the system function (for example electric power). Here, the operability of components depends on the flow in another layer or consumes a transported good of another layer of the model. Importantly, this approach is similar to the way interdependencies are modeled in Sharkey et al. (2016), such that they can capture input-output relationships and restoration interdependencies.

The model presented by Enayaty Ahangar et al. (2020), measures network function via the flow in the network and how efficiently this flow is being routed through the network. This is possible via min-cost network flow optimization, where cost can be monetary or the amount of time needed. The authors demonstrate the model using generic interdependent infrastructure systems with flow optimized as interdependent multi-layered network flow (IMN) model as a mixed-integer programing (MIP) model to maximize performance.

2.2.2 Operator Models for Critical Infrastructure Systems

We build on this literature to apply interdependent infrastructure modeling and analysis methods to CIS. Here, we review operator models for CIS without interdependencies to describe their normal function and analysis. Our review focuses on lifeline infrastructure systems relevant to island and military installation operations, i.e., fuel, electricity, water, transportation, and telecommunications systems. Here we overview only the most recent and relevant work. We refer the author to Sharkey et al. (2020) for an broader review of operator models and their relationship to CIS, vulnerability, and resilience.

Fuel

One of the most well-studied examples of an operator model is the notional fuel model presented in Alderson et al. (2015) (Figure 2.3). This operator model was developed to show the output of AD and DAD methods for resilience analysis. This is a very simple model with only two supply nodes (black) and 14 demand nodes (white) with a few redundant connections to ensure the network is N-1 reliable. It is used to analyze the influence of damaged connections between the nodes and show how well the system operator is able to adapt to the situation. The network operations is similar to a real fuel system, with the objective to minimize the cost of supply.

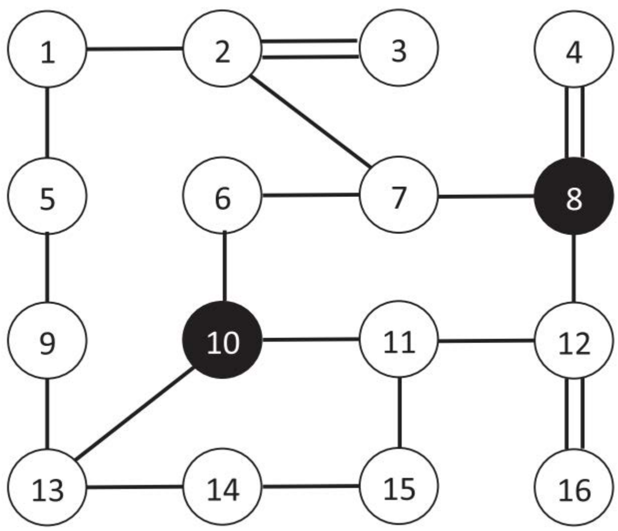

Figure 2.3. Notional Fuel Network from Alderson et al. (2015). This network is an example operator model for a fuel system. Black nodes are supply nodes and white nodes are demand nodes.

Operations are measured modeled and solved as a linear program. Originally implemented and solved in General Algebraic Modeling System (GAMS) (GAMS Development Corporation 2020) by Alderson et al. (2015) and then Dickenson (2014), it was later implemented using Pyomo (Hart et al. 2017) by Ruether (2015) for modeling interdependencies in a fuel and electric power network. The optimization in the fuel network is done by minimizing cost and assigning cost for each arc, a unit of fuel is pumped through and extra cost if a nodes' demand is not met. Additionally there is a maximum capacity per arc assigned. This guarantees that the shortest possible path in the network is chosen with the priority that all possible nodes get supplied.

Electric Power

A very popular CIS for study is an electric power network. In general, electric power networks consist of three stages. First, the electric power is generated by an electric power plant of any type (e.g., gas, coal, nuclear, wind, solar, water). For the long-distance transport, and to keep losses as small as possible, the voltage is stepped up to high-voltage for long-distance transmission. This transformation of the voltage happens at transformers and substations. Near the consumer, the voltage is stepped down for distribution to households or large scale customers (e.g., industry and businesses). This is all connected in a network, often where different voltages stages are separated by substations (Bunn 2018).

Often, transmission and distribution networks each use a different operator model. For transmission, Direct Current Optimal Power Flow (DCOPF) is used because either it is a direct current line or networks are assumed to have balanced flows across all phases, making many physical effects of related to impedance negligible. This is because the position of all three phases of the power line are being rotated, so that the physical (electromagnetic) impacts on the power transmission cancel out.

For the distribution stage on shorter distances the physical effects do not cancel out and the more complicated Alternate Current Optimal Power Flow (ACOPF) model should be used to compute these effects and get more realistic results of the unbalanced loads in the electric power network (e.g., Nagarajan et al. 2016). Petri (2017) used Pyomo to solve a ACOPF based model with assigning cost for each shed kilowatt (KW) load and minimizing the sum of this cost.

Water

The most common operator model for potable water systems is the Water Distribution Network (WDN). The structure and function of most WDNs follow the system in Figure 2.4. Water is either withdrawn from a natural fresh water source (e.g., lake or groundwater) or sea water is converted into fresh water with desalination or reverse osmosis. Afterwards water is treated for human consumption in a water treatment plant with different types of filters, UV-illumination or chlorination, and is then pumped into a storage tank. These storage tanks are mostly on an elevated position (e.g., on a hill or as a tower) and supply a community with water by gravity, supported by pumps for the correct water pressure.

The computing the behavior of a water distribution network is done with water network simulation. Bunn (2018) used the Water Network Tool for Resilience (WNTR) (Klise et al. 2018), a Python-based (Python Software Foundation 2001) package for simulating and analyzing the resilience of a WDN, based on the EPANET software application (U.S. Environmental Protection Agency 2000). WDN are modeled by using pipes, pumps, tanks and sources. Pipes are connected by junction nodes, where the withdrawal of water takes place. These elements together are used by the simulation using a pressure dependent demand (PDD) model to compute the flow of water via hydraulic balancing.

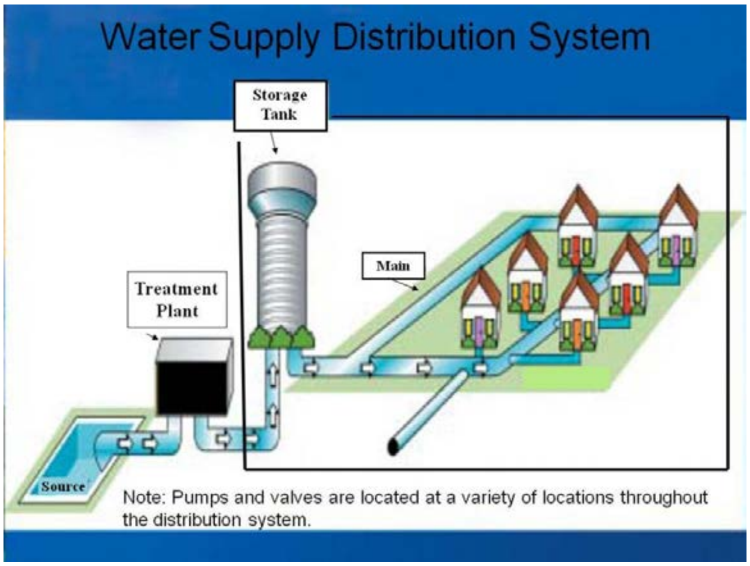

Figure 2.4. Drinking Water Distribution System. Water is pumped from a water source, treated for human usage in a treatment plant, and stored in an elevated tank to supply households by gravity. The flow of water is supported by pumps. Source: U.S. Environmental Protection Agency (2020).

Transportation

Mobility across transportation systems can also be represented with operator models. One common example is the movement of vehicles and supplies over surface roads. Good (2019) built a network optimization model of a transportation network, using the streets on the island of St. Croix in the USVI. The purpose was to model the traffic after an extreme event disaster and determine which part of the island has the most difficult reaching locations of disaster supplies (e.g., gas stations, groceries, and hardware stores). This model was built as a minimum cost multi-commodity network flow model. System functions is determined by network congestion, such that flow is slowed down with increasing traffic until a traffic jam arises. The objective function contains the minimization of the number of vehicle-hours spent on each arc (street) with a penalty function for dropped transportation due to congested streets. Each arc has a capacity, based on the type of street (dirt, rural, urban and highway). This problem was also solved using Pyomo.

Telecommunications

Telecommunication networks, such as backbone internet and wireless networks, can also be modeled as a minimum-cost network flow problem. Martin (2014) created a network flow problem on a fictitious island Dystopia (described in detail in Alderson and Darken 2019). Internet users are connected via their Internet Service Provider (ISP) to a network node and their traffic is being routed through the network to the target node. Connections between the nodes are assumed as optic fiber connections with negligible influence on the transmission time but with capacity restriction (data bandwidth). The part in this network with the most impact on the speed are network nodes, because at each hop, where data traffic is routed from one connection to the other, the router has to analyze each data package to find the correct destination connection, which consumes a small amount of time. The objective function of this model is to minimize the number of hops (traversed router).

The minimum hop model was used to determine worst-case failures with a network interdiction problem for destroyed connections. This was modeled in GAMS (GAMS Development Corporation 2020) and used to determine network hardening requirements.

2.2.3 Interdependent Operator Models

One of the goals of this thesis is to develop standardized ways to connect independent operator models together for interdependent analysis. In general, dependencies and interdependencies are only studied for pairs of infrastructure systems. We review some well-studied examples motivating this work.

Figure 2.5 presents one approach to create two interdependent infrastructure models. In general, interdependent operator models are the result of combining two pre-existing network flow model formulations. As a motivating example, we consider the case where a fuel network depends on a electric power network. The grey model represents a fuel network that depends on electricity to operate, where operator objectives and constraints for fuel delivery are combined with constraints and parameters for electric power dependencies. This model can be studied on its own to understand the function and vulnerability of a fuel system when electric power is unavailable. For interdependent analysis, the grey model is combined with a electric power model that determines how electricity is delivered across a electric power network including assets in the fuel system (e.g., pumps). Together, the two form an interdependent network flow model that is based entirely on model elements inherited from the existing formulations, such as a shared objective, flow constraints, and dependency constraints from the fuel model.

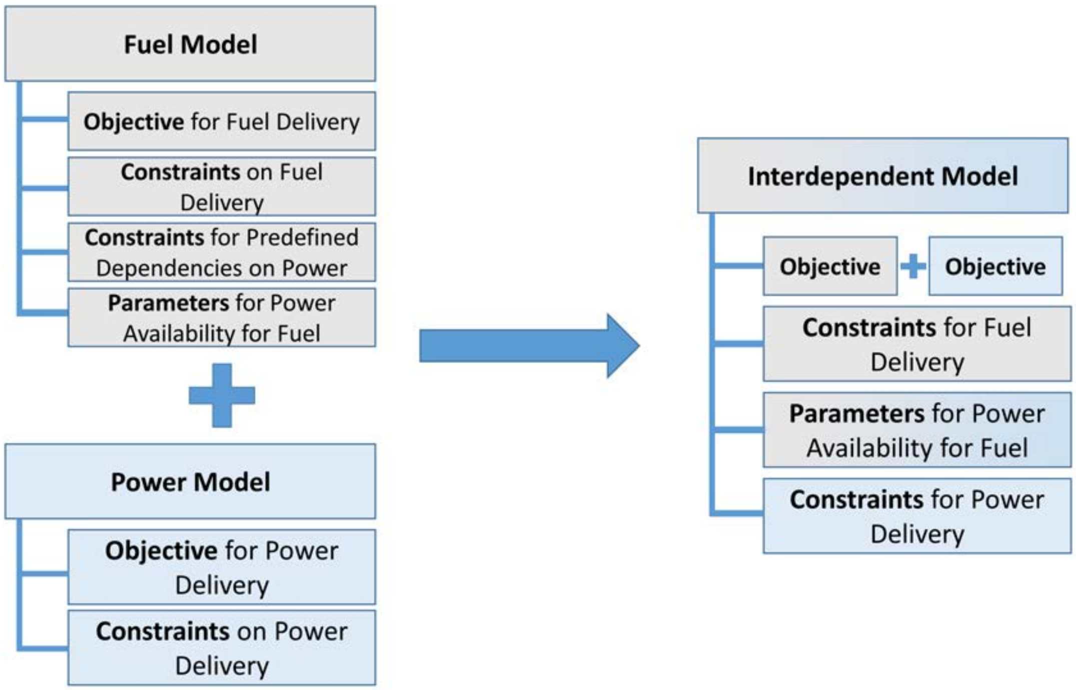

Figure 2.5. Common Approach to Create Interdependent Operator Models. Interdependent operator models are often the result of combining two standalone operator models. Here fuel and electric power models are considered as a motivating example. Dependencies of the fuel model on electric power delivery are included in fuel model formulation. Then, the two models are combined with a shared objective, constraints for network flows, and constraints for dependencies. Essentially all interdependent operator models in the literature are created with a similar process.

Fuel and Electric Power

A combined fuel and electric power network was modeled by Dickenson (2014) in GAMS (GAMS Development Corporation 2020) and then adapted to the Python-based Pyomo by Ruether (2015). Both independent models (fuel and electric power) were modeled and solved independently, then connections were added and both models were solved together as a combined network optimization model. The interdependencies across systems include the need for electric power generators to access fuel from the fuel network to function. If the available fuel is lower than a specified threshold, the generator does not produce any electric power. There are also fuel connections (arcs) that need electric power to be able to transport fuel, so if the available electric power is lower than a specified threshold, the fuel pump is not working and fuel is not transported. Thus, the modeled interdependencies included in this model are exclusively physical interdependencies due to shared supply and demand needs. The combined operator model analyzes the impact of failures in one of the systems on the other system, such that cascading failures can happen and considered in vulnerability analysis. For this connected model two minimal cost network flow models were used, so that the model consists of sub-models and additional constraints. The analysis with these models has important implications for the resulting behavior of the connected systems. For example, Dickenson (2014) shows that changing how fuel and electric power connections are modeled, the interdependent model might converge to suboptimal solutions or fail to converge at all.

Water and Electric Power

Bunn (2018) combined an electric power network flow optimization model with a WDN. The water model was built using WNTR and combined with the Pyomo electric power model from Petri (2017) using ACOPF. Bunn (2018) ran the two models for a 24-hour time-frame and updated them each hour, so that the water model results were passed to the electric power model, then this model ran and the results were passed back to the water model. He modeled physical (e.g., water pump using electricity) and geographic (i.e., co-located node) dependencies. For testing this combined simulation/optimization he used three simple excursions (power outage, water demand spike and water demand drop).

A similar problem was also analyzed by Zuloaga et al. (2020). They combined an electric power network with a WDN. Both infrastructure networks rely on each other, where water is used to cool electric power plants and electric energy is used to pump the water. They used EPANET (U.S. Environmental Protection Agency 2000) (on which WNTR is based) to complete WDN simulation, and optimized the flow in this network by using MATLAB (Higham and Higham 2017). To solve the electric power flow and unit commitment problems in the electric power network, they combined different techniques. The unit commitment (which power plant produces when) is solved every 24 hours with a module which is programmed in A Mathematical Programming Language (AMPL) (Fourer et al. 1990) and the optimal power flow is computed by using the General Electric Company (GE) Positive Sequence Load Flow (PSLF) software. WDN optimization was done by a genetic algorithm and was run for four weeks (672 h). The example computations were done on a toy network, where the electric power network was composed of five power plants with different generator fuel types (nuclear, coal and gas), each having a storage tank for cool water. These were supplied by fresh water and recycled water, each being pumped with pumps needing electric energy. Additionally there was fresh water provided to two cities.

Electric Power and Transportation

Goldbeck et al. (2019) combined a electric power and transportation network to assess the interdependencies of London's metro and electric power network given a simulated flooding incident. For this, an asset failure simulation was combined with a network flow optimization model via a HLA simulation (Figure 2.6). First, before running the general simulation and optimization model, stochastic asset failure scenarios were generated including their failure propagation probabilities to other assets, based on diverse interdependencies. Then, both network flow optimization models were solved in time-steps (e.g., hours) including a planning horizon with influence from the asset failure scenarios (e.g., unmet demand is moved to the next time-step) and their already completed repairs.

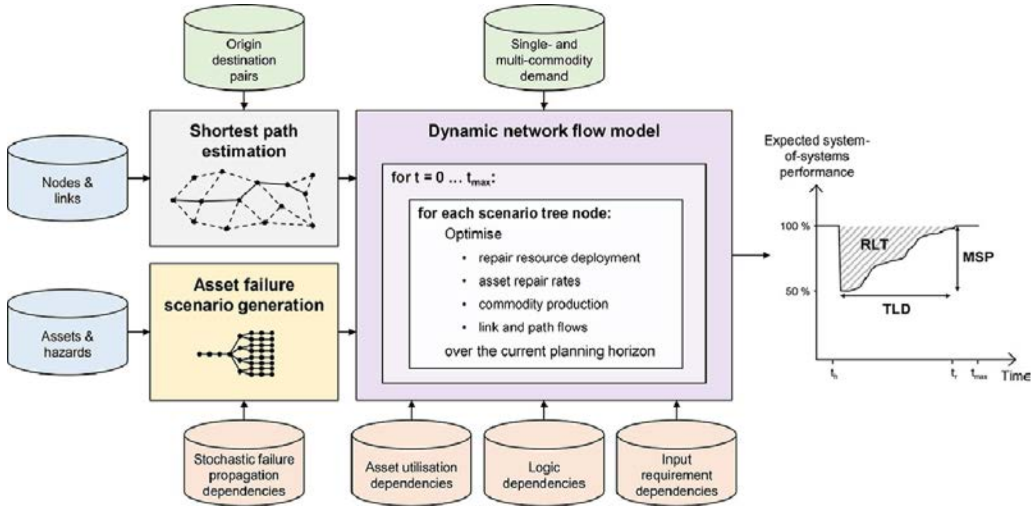

Figure 2.6. Interdependent Infrastructure Modelling Framework from Goldbeck et al. (2019). The author's modelling framework is a good example of a standardized approach to consider system failures and apply them on a dynamic network flow model to analyze interdependencies.

Overall, there is a diversity of models and methods to represent CIS as operator models and assess their interdependent vulnerability. Accordingly, there are numerous ways to implement frameworks for connecting and assessing operator models. We review some programming implementations to describe available software and programming packages that support thesis goals.

2.3 Implementing Operator Models

To simplify our review and methods development, we focus on object oriented programming-based implementations. There are several publicly available Python software packages available for simulating or optimizing infrastructure operator problems. Despite packages for optimizing network flow, assessing damage probabilities, and their effects, to the best of our knowledge, there are no available packages with the capabilities for interdependent infrastructure modeling we propose in this thesis. Still, four packages provide an overview of available software representative of the best available approaches to operator modeling.

2.3.1 PyIncore: Python Interdependent Networked Community Resilience Modeling Environment

PyIncore is a Python package developed by a large number of universities funded by the National Institute of Standards and Technology (NIST) (Center for Risk-Based Community Resilience Planning 2020). It is a Python-based interface to access the Interdependent Networked Community Resilience Modeling Environment (INCORE). This environment enables damage and functionality assessment and also has some economic and recovery functions. A large database of input-data is available and it is suggested to save the used input data on the INCORE-Server. For using the package, a previously generated and unlocked account is necessary and used for authentication before each use of the software. The analyzing approach is risk-based, using different scenarios and comparing them. The mode of operation is that a specific hazard is applied on geospatially assigned infrastructure (defined by building data and fragility data). This yields a damage value for every single infrastructure in the model. From this damage data the functionality of buildings, the economic impact and the needed recovery force can be estimated. At this time the hazards are limited to earthquakes, tsunamis, tornadoes and hurricanes.

PyIncore has very modular implementation in Python, which facilitates the re-usability of functionalities. The functionality is based entirely on the geographic position, so it is not directly comparable to a physically interconnected network flow analysis, but geospatial interdependencies are an interesting influence on models to consider. The input-file datatype is JavaScript Object Notation (.json), so very similar in usability as Comma-Separated Values (.csv). PyIncore is designed to assess damage probabilities of independent buildings and structures to different types of hazards.

2.3.2 EGRET: Electrical Grid Research and Engineering Tools

The second package is the Electrical Grid Research and Engineering Tools (EGRET) (Knueven et al. 2019). This Python package is based on Pyomo and used for optimizing the power flow in a electric power network using DCOPF or ACOPF and for optimizing the unit commitment problem. With this the allotment of the use of different generators is optimized to reach a specific target like fulfilling the energy demand or minimizing cost. This package is exclusively limited to electric power networks and does not seem to have support for other types of infrastructure networks (e.g., water, transport, communication).

The implementation of EGRET is very modular, each module can be easily reused and it has an effective installation procedure. The python objects are documented with docstring and for testing the source code after changes, unit testing is implemented by using PyTest.

2.3.3 LANL-ANSI: Los Alamos National Laboratory's Advanced Network Science Initiative

The next package is the Los Alamos National Laboratory's (LANL) Advanced Network Science Initiative (ANSI), called LANL-ANSI (Tasseff 2020). This is not a single optimization framework or software, but a collection of multiple similar optimization projects. Single infrastructure network optimizations alongside with combined network optimizations are available (e.g., gas, electric power, water and combined gas and electric power).

Projects in LANL-ANSI are implemented in the Julia Programming Language (Bezanson et al. 2017) which is used for numerical analysis, and even if it does not fit in our scope, this package is interesting to revisit. Input data can be imported from broadly used file types, like .dss for electric power networks and .inp for water networks. When using systems combining multiple infrastructure networks, the interconnection is modeled in a separate data file (for example using the JavaScript Object Notation [.json]). Input file types highly depend on the used module, they do not have to be similar.

When using these modules it is not straightforward to align models and data structures. The language Julia is also new (appeared in 2012) and not so broadly used, so that it is not as easy to find information, tutorials and examples in comparison to more widely used languages.

2.3.4 PySP: Pyomo Stochastic Programming

The last revisited project is Pyomo Stochastic Programming (PySP) (Watson et al. 2012). PySP is part of the standard Pyomo package and is a Pyomo modeling extension used to solve stochastic programming optimization problems. These problems are optimization problems with uncertainty, mostly computed for projecting into the future. Either different scenarios or different nodes in network problems are modeled and given a stochasticity, so a probability of a tree branch in addition to the deterministic base model.

2.4 Our Approach

We build on past work to develop new analyses and assessments that advance the literature and practice of interdependent infrastructure analysis. Our goal is to create a framework to be able to model dependencies and interdependencies in a standard form to reuse the models, when combining them with other models. For reaching this goal, we will:

1. Develop a Python-based framework for linking two network flow models together.
2. Develop a toy network for two small infrastructure systems to demonstrate methods.
3. Implement or reuse previously studied, realistic networks to validate methods.
4. Test our framework with a model of a third infrastructure system that was not intended for interdependent infrastructure analysis.

It is very important that this framework is able to perform analysis with network optimization models using Pyomo.

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CHAPTER 3:
Interdependent Infrastructure Model

In this chapter, we develop a framework for modeling interdependent infrastructure systems. We present methods from the literature for interdependent network flow optimization and relate their formulation to critical infrastructure systems. However, past methods assume full knowledge of system interdependencies prior to model development and provide limited guidance for combining models developed without prior knowledge of interdependencies. We expand on these methods to create a generic approach to combine infrastructure network flow models. These generic methods support the analysis of infrastructure networks created without prior knowledge of interdependencies and support extensible and applied analyses, such as the effect of directional dependencies (one system depends on the other, but not vice versa) or the inclusion of non-optimization models (e.g., simulation models). This new approach also supports well-established methods for network vulnerability assessment.

3.1 Interdependent Network Flow Models for Critical Infrastructure Systems

Our interdependent infrastructure methods are based on the work of Enayaty Ahangar et al. (2020) for interdependent multi-layered network flow (IMN) modeling and analysis. This model formulation is generic for any network flow system and is based on the interdependent layer network (ILN) problem first formulated by Lee II et al. (2007). We relate this generic approach to critical infrastructure systems by identifying dependencies that occur in real networks and relating them to model primitives.

3.1.1 IMN Model Formulation

The following formulation is reproduced from Enayaty Ahangar et al. (2020):

Indices and Sets

K	the set of layers
N^k	the set of nodes in layer $k \in K$

A^k	the set of arcs in layer $k \in K$
$G^k = (N^k, A^k)$	the directed network representing layer $k \in K$

Parameters [units]

u_{ij}^k	the flow capacity on arc $(i, j) \in A^k$
c_{ij}^k	the cost per unit flow of commodity $k \in K$ on arc $(i, j) \in A^k$
f_i^k	the reward when node $i \in N^k$ is operable in layer $k \in K$
$d_i^{kk'}$	$(k \neq k')$: the required consumption of commodity $k \in K$ at node $i \in N^k \cap N^{k'}$ for node i to be operable in network layer $k' \in K$; $(k = k')$: the supply (if $d_i^{kk'} < 0$) or demand (if $d_i^{kk'} > 0$) of commodity $k \in K$ at node $i \in N^k$

Decision Variables [units]

x_{ij}^k	the flow on arc $(i, j) \in A^k$
y_i^k	whether (1) or not (0) node $i \in N^k$ is operable in layer $k \in K$

Formulation

$$\max \sum_{k \in K} \sum_{i \in N^k} f_i^k \cdot y_i^k - \sum_{k \in K} \sum_{(i,j) \in A^k} c_{ij}^k \cdot x_{ij}^k \tag{3.1}$$

$$\text{s.t.} \quad \sum_{(i,j) \in A^k} x_{ij}^k - \sum_{(j,i) \in A^k} x_{ji}^k \leq -d_i^{kk'} \cdot y_i^{k'} \forall k, k' \in K, \forall i \in N^k \cap N^{k'} \tag{3.2}$$

$$x_{ij}^k \leq u_{ij}^k \cdot y_i^k \qquad \forall k \in K, \forall (i, j) \in A^k \tag{3.3}$$

$$x_{ij}^k \leq u_{ij}^k \cdot y_j^k \qquad \forall k \in K, \forall (i, j) \in A^k \tag{3.4}$$

$$y_i^k \in \{0, 1\} \qquad \forall k \in K, \forall i \in N^k \tag{3.5}$$

$$x_{ij}^k \geq 0 \qquad \forall k \in K, \forall (i, j) \in A^k \tag{3.6}$$

Discussion

The basis of this model is a network object consisting of nodes (N^k), arcs (A^k), and their directed relationships (G^k). In addition to standard network models, this multi-layer model includes layers (K), where each layer or combination of layers can represent an infrastructure system.

Network flow is governed by optimization to maximize the reward f_i^k for ensuring system elements are operable while subtracting transportation costs c_{ij}^k for each usage of an arc constrained by capacity u_{ij}^k. The supply or demand of a node, as well as the interdependence are controlled by the parameter $d_i^{kk'}$. Decision variables are x_{ij}^k for the flow on an arc and the binary variable y_i^k for the operability of a node.

With Constraint (3.2) the supply or demand of a node is included in the model. The arc capacity and the operability, controlled by the interdependent node is controlled by constraints (3.3) and (3.4). And at the end the non-negativity constraint for arc flow (constraint 3.6) and the operability of a node (binary constraint 3.5) is included in the model.

This very basic formulation enables an optimization model for lots of different types of infrastructures and can be used as a basis for more complex models.

3.1.2 Modeling Infrastructure Dependencies

Lee II et al. (2007), Dixon (2011), and Enayaty Ahangar et al. (2020) identified ways to relate the IMN model to infrastructure dependencies:

- **Input dependence:** When one infrastructure depends on the commodity of another infrastructure, for example a water pump needs electricity to operate. Here, the IMN model would include $d_i^{kk'}$ from layer k representing electricity to layer k' representing water. When enough electricity is delivered from the electric power network to the water network, $y_i^{k'} = 1$ and the water system node is operational.
- **Mutual dependence:** Multiple infrastructures are dependent on each other, for example a fuel network needs electric energy to work and an electric power network needs fuel to produce electric power. These dependencies can be implemented similarly to input dependence.

- **Shared dependence:** Multiple infrastructures are dependent on one node or arc in an infrastructure, for example a water pump and an intersection are powered by the same node of an electric power network. These dependencies can be represented similar to input dependence as $d_i^{kk'}$ are independent for each combination of layers k and k'.
- **Exclusive-or dependence:** This dependence only allows one of multiple dependent nodes to work, for example a railroad crossing, where either a train can cross or vehicles can cross. These dependencies can be implemented by constraining combinations of binary variables y_i^k.
- **Co-located dependence:** Components of multiple infrastructures in the same geographical region are either working or not depending on shared failures, for example an electric power substation and a subway stations are not usable due to flooding of a co-located region. These dependencies can also be implemented by constraining combinations of binary variables y_i^k.

While these dependencies capture many critical infrastructure relationships, streamlining their implementation for interdependent analysis requires greater consideration of infrastructure model structure. The representation of infrastructure interdependencies depends on the physical relationships among systems and their representative model primitives. Real infrastructure models represent different assets as arcs and nodes depending on the services they provide. The failure of a node or arc in one network may have direct effects on the functioning of dependent systems and network effects and can impact interdependent operations. To relate real system to IMN dependencies, we list several examples of node and arc dependencies in Table 3.1 and the different effects of their failures.

Table 3.1. Critical Infrastructure Network Dependencies.

Infrastructure Model Elements & Effects

Arc		**Arc**
Pipe breaks	→	Road flooded
Powerline falls	→	Road blocked
Node		**Arc**
Power demand unsatisfied	→	Water pump shut down
Power demand unsatisfied	→	Fuel pump shut down
Node		**Node**
Power demand unsatisfied	→	Intersection jammed
Fuel demand unsatisfied	→	Power generator shut down
Arc		**Node**
Road jammed	→	Telecom repair impossible
Telecom broken	→	Power substation shut down

Infrastructure node and arc relationships are important to consider because they help guide the development of more extensible model formulations than those found in the literature. As shown in Table 3.1, choice of infrastructure model elements and their failure effects influence how to connect two infrastructure models together. For example, power demand (represented as a node in a electric power flow model) can impact the operations of arcs (if they represent pumps in water and fuel systems) or nodes (if they represent intersections in transportation systems).

However, linking models together for interdependent analysis is possible with multiple implementations. For example a water pump can be modeled with a arc-on-node dependency as shown in the table, such that when a power demand node receives sufficient electric power, the water pump arc is able to move water. Another possibility would be to model it as a node-on-node dependency, so that multiple pumps (condensed into a node representing a pumping station) are all powered by the same electric power demand node and are only working if the needed demand is met. Depending on the scale of models and analysis, its possible to need both implementations.

3.2 Generic Structure of a Combined Model

The goal of this work is to develop a method to model dependencies and interdependencies in a simple, adaptive way that enables a modeler to use either standalone or interdependent models for analysis. Whereas the IMN model formulation supports interdependent analysis, constructing and solving an IMN problem often assumes knowledge of model objectives and interdependencies prior to model build and solve. Yet, many infrastructure models are constructed as independent, standalone models, and interdependencies are only considered after initial model construction. With these pre-built models, interdependencies cannot be modeled freely and it may be difficult to link systems together.

Instead, we build on the IMN formulation and use a more extensible approach utilizing the object oriented nature of Pyomo optimization models (Hart et al. 2017) in the Python programming language (Python Software Foundation 2001). Figure 3.1 presents the goal of our approach with fuel and electric power networks as a motivating example. similar to the IMN mode, past interdependent operator models assume perfect knowledge about networks and dependencies during model development, where all model elements are inherited from pre-existing problem formulations (see Figure 2.5), In contrast, we can use the object-oriented nature of Pyomo to add and change model elements for dependencies to pre-existing models by modifying existing objectives and adding indices, parameters, variables, and constraints. For the purposes of this work, we call these new dependent and interdependent models *combo-models*.

The key difference with this approach is that neither the fuel model nor electric power model in Figure 3.1 need to comprise predefined dependencies to form an interdependent operator model. In other words, dependencies and interdependencies are not inherited from pre-existing models, but added in when forming the combo-model. This approach allows a user to take infrastructure models created for a single system in Pyomo (e.g., an electric power network) and connect it to other standalone models (e.g., a fuel network). Each standalone model becomes a sub-model object where constraints for interdependencies are added and the joint objective function of both infrastructure systems are solved simultaneously.

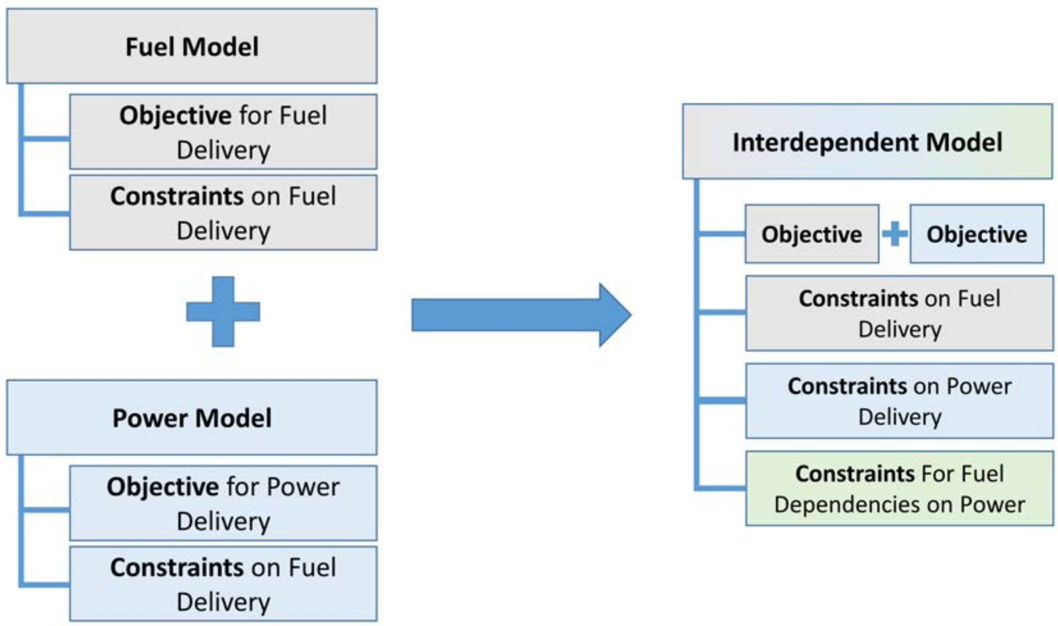

Figure 3.1. New Approach to Create Interdependent Operator Models. Previous approaches to create interdependent operator models relied on inheriting model elements from pre-existing model formulations (see Figure 2.5). In contrast, we present a new way to form interdependent operator models that does not inherit dependency constraints from pre-existing models, but rather adds them in based on user input. The result is not requiring predefined infrastructure dependencies prior to model creation and analysis. This small change in approach has meaningful implications for interdependent operator model development and analysis.

3.2.1 Generic Combo-Model Formulation

We introduce notation for linking two models together to create a formulation for combo-models. First, we assume that there are two standalone Pyomo model objects representing infrastructure network flow problems — *model1* and *model2*. We construct dependencies in a single direction at a time, such that there is a dependent model (DM) depending on the function of another serving model (SM) providing a commodity for the DM to function (e.g., if *model1* depends on *model2*, *model1* is the DM and *model2* is the SM).

To link Pyomo model objects together for interdependent analysis, first we define new sets, parameters, and decision variables that control dependencies.

Indices and Sets

$DepE \subseteq G^{DM}$	dependent elements of network DM needing commodity from SM
$ServE \subseteq G^{SM}$	serving elements of network SM delivering commodities to DM

Parameters

$Thresh_d$	commodity threshold in *DM* to be met for $d \in DepE$ to function

Decision Variables

T_d	1 if $d \in DepE$ is functional, 0 otherwise [binary]

Discussion

We define four new model elements when creating dependencies. First, a new set of network elements of the DM which are dependent on a commodity flow from the SM denoted by the subset $DepE$. Similarly, we define a subset of network elements of the SM that provide commodity services to the DM as the subset $ServE$. Both subsets can be either nodes or arcs, depending on the element-effects relationships between the DM and SM (e.g., those in Table 3.1). $Thresh_d$ defines a functional threshold for the dependency model element $d \in DepE$ requires of the flow commodity from the SM to be operational. The binary decision variable T_d acts as a switch to set the dependent model element d as working or not working based on the function of the SM.

These model elements relate to the IMN model, but have key differences that enable more extensible implementations and interdependent solves. $Thresh_d$ and the binary variable T_d serves a similar role to $d_i^{kk'}$ and y_i^k in an IMN, respectively. However, in the IMN formulation, $d_i^{kk'}$ defines both flow demands and commodity requirements for a node to function in a DM (alias k). In contrast, the functional threshold $Thresh_d$ can be a different value than flow requirements, such as when a minimum flow is required for an infrastructure asset to operate (e.g., the electricity to turn a pump on), but total demand for operation may be higher (e.g., the final pump electricity requirements are greater). This approach supports linking more realistic infrastructure models for assessing operations during disasters, such as flow models with the objective of minimizing load shed rather than maximizing asset use and minimizing flow costs.

Moreover, $DepE$ and $ServE$ are any subset of nodes or arcs defined after a DM and SM model are constructed. While flow restrictions due to functional interdependencies on nodes and arcs can be included in the IMN formulation, this would require node splitting strategies or the addition of intermediate flow networks k'' for node-node and arc-arc dependencies. The use of subsets from existing models simplifies the overall implementation and enables easy model construction and solves.

With these additional model elements, we define a new interdependent *combo-model* using two existing Pyomo model objects.

Formulation

$$\min_{DecVar[model1]+[model2]} \quad Obj[model1] + Obj[model2] \tag{3.7}$$

$$\begin{aligned}
\text{s.t.} \quad & Constraints[model1] \ \& \ Constraints[model2] \\
& Thresh_d \cdot T_d \leq \\
& \qquad \sum_{(k,s)\in Arcs^{SM}} Y^{SM}_{(k,s)} \\
& \qquad - \sum_{(s,m)\in Arcs^{SM}} Y^{SM}_{(s,m)} && \forall d \in DepE, s \in ServE && (3.8) \\
& 0 \leq X^{DM}_d \leq Cap^{DM}_d \cdot T_d && \forall d \in DepE && (3.9) \\
& T_d \in \{0,1\} && \forall d \in DepE && (3.10)
\end{aligned}$$

Discussion

We use the object-oriented nature of Pyomo optimization models to combine infrastructure networks together. Some elements from *model1* and *model2* are retained the combo-model. The objectives of both standalone models are combined by adding them if they have both the same optimization sense (minimizing or maximizing) or by subtracting them if they have different optimization senses. All constraints from the original models are also retained. This multiobjective formulation uses implicit weighting of 1 for each objective (i.e., flow costs in each network are assumed to be equal and independent). This can be changed by setting weights for each objective function or using a different multiobjective relationship (e.g., division).

Several constraints are added to the combo-model for interdependent analysis. First, (3.8) is used to decide if there is enough commodity at element s to switch T_d to 1, allowing d to be operable. The needed threshold for this is set by parameter $Thresh_d$. The control of component d in the DM is constrained by (3.9), where X_d^{DM} is either a flow decision variable if d is an arc or a demand decision variable setting the produced or consumed commodity amount at a node. Cap_d^{DM} is the associated maximum capacity of this network element. With constraint (3.10), T_E is defined as a binary variable.

3.2.2 Combo-Model Implementation in Python

The combo-model formulation is enabled by the object oriented nature of the Python programming language and Pyomo optimization languages. In general, creating a new model with sub-models and interdependencies is complicated, lots of factors for each dependency need to be considered. Our generic combo-model structure simplifies and generalizes this process by a pre-defined structure. We implement this approach in Python to demonstrate its flexibility and standardize a framework for modeling interdependencies, using Pyomo for this task for the following reasons:

- Pyomo is an optimization-modeling language, widely used for optimization models (Hart et al. 2017);
- Pyomo and Python are open source, very good suitable for rapid prototyping and can be learned very fast;
- Pyomo allows flexible use of optimization solvers.

We used the commercial solver CPLEX (IBM Corporation 2019) by IBM for our computations because of its good performance.

3.2.3 Combo-Model Generator Function

Pyomo optimization models are often formulated once and then used multiple times with different input data to compare different model configurations. We implement a user-friendly combo-model generator function, that is used as a script to simplify the generation of a combo-model object file from two present Pyomo models. The resulting combo-model object file is then used to load this combined model in Pyomo for the analysis. An example use of the combo-model generator function is shown in Figure 3.2.

```
COMBO-MODEL-GENERATOR
=====================
Name for generated file (.py): model1 on model2.py
#####
How many dependencies? (1-4): 1
#####
Dependency 1:
Directions: model1(2) depends on model2(1) --> 1on2 (2on1)
Enter the direction of the dependency: 1on2
Types: node-on-node: nn / node-on-arc: na / arc-on-node: an / arc-on-arc: aa
Enter the type of the dependency: an
Flow variable and arcs of model2:
Var of model2:
['x', 'y']
Enter the flow variable of model2: x
Set of model2:
['K', 'N', 'A', 'G']
Enter the arc set where the flow is on of model2: A
Dependent element (generating node / flow variable of arc) and capacity of model1:
Var of model1:
['x', 'y']
Enter the dependent generating node / flow variable of model1: x
Param of model1:
['u', 'c', 'f', 'd']
Enter the dependent node/arcs capacity of model1: u
#####
```

Figure 3.2. Combo-Model Generator Function. Given two Pyomo models as function inputs, the combo-model generator asks a user simple questions to generate an interdependent network flow model. User input is underlined in red. In this figure, we assume model elements are from the IMN and combo-model formulations.

The combo-model generator function is called from the command line or within a script and takes two network flow models as inputs. Then, the function prompts several areas for modeler input as shown in red in Figure 3.2. First, the user names a python script (.py) filename for saving the model to a file. The user then designates which model is the DM and SM via dependency direction (e.g., *model1* dependent on *model2* is written as 1on2). The user then decides which types of model elements are dependent on each other (e.g., *an* means arcs dependent on nodes). The user then chooses the flow variables and sets for defining $ServE$, followed by the similar prompts for defining $DepE$. For each step, the function shows the user the appropriate data-structure to choose from and prevents typos.

The combo-model generator function produces a (.py) file with a built-function for a Pyomo combo-model object and the correct number of arguments to populate with interdependency data. To conduct interdependent infrastructure analysis, a user must import this new model object and populate with data to explicitly define $DepE$, $ServE$, and $Thresh_d$. Interdependency data is input as edge list in a Pandas DataFrame (The Pandas Development Team 2020), where the dependent node is used as the index.

3.3 Interdependent Network Vulnerability Analysis

In this work, the purpose of constructing interdependent network flow problems is to assess system function and vulnerabilities. Where network flow optimization yields a steady-state snapshot the operations of an infrastructure, a more interesting question is measuring how vulnerable the system is with respect infrastructure disruptions and failures.

3.3.1 Worst-Case Vulnerability assessment of a Single Network

Alderson et al. (2014) proposes interdiction models as a bi-level or tri-level optimization problem for identifying the worst-case failures in an infrastructure system. An overview of the different available approaches is shown in Figure 3.3. The structure of modeling this problem is to define the failure events and to incorporate them into the model. Afterwards the attacker model is formulated to maximize the cost of a minimal cost network flow problem with the available attack budget $x \in X$ (starting at the bottom of Figure 3.3 going up to the left). This analysis finds the worst-case failures that increasing the cost of infrastructure operations much as possible.

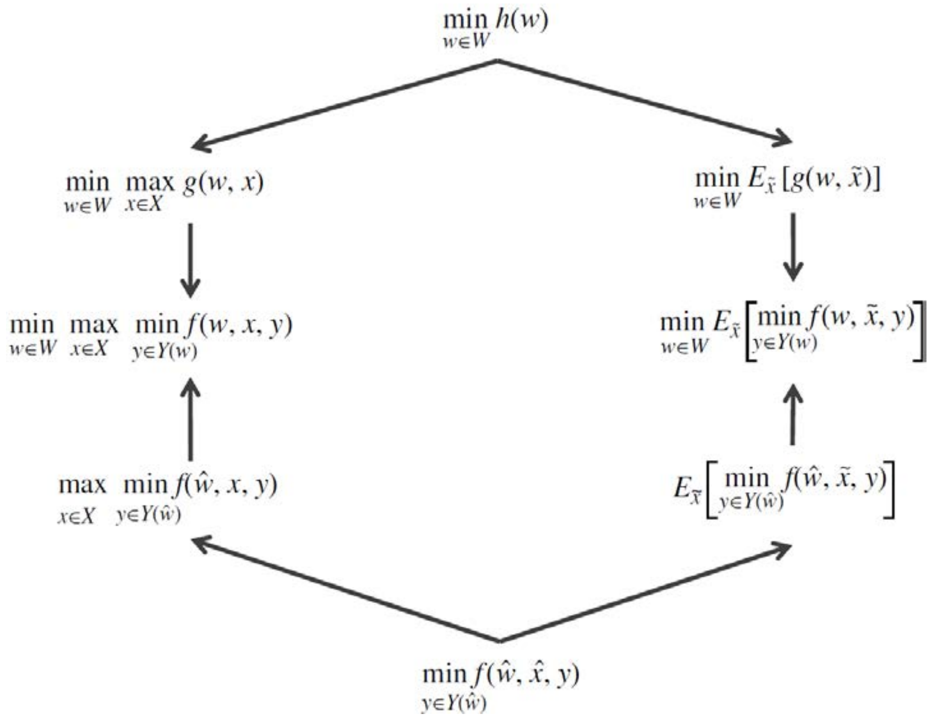

Figure 3.3. Path of Assessing and Improving Operational Resilience. Either from a top-down or bottom-up view, using different optimization techniques: deterministic mathematical programs (left) or stochastic models (right). Source: Alderson et al. (2014).

The next step from an infrastructure operators' point of view is to strengthen the infrastructure and mitigate failures with a limited budget. This is the third layer optimization with choosing the best design $w \in W$ to minimize the maximum possible cost by attacks. This approach is the suggested bottom-up approach by Alderson et al. (2014), where the considered infrastructure system is being modeled at the component level and the functioning of the system depends on all components and how they work together.

In comparison to this approach, it is possible to take a top-down view (starting at the top of Figure 3.3) and have the objective to minimize cost by improving the operational resilience function $h(w)$ by choosing a design w. But there are difficulties with this approach. Choice of units for $h(w)$ measured and presenting the different designs w? is difficult.

Both approaches, top-down and bottom-up, can also be applied, when having the case of non-deliberate events, that are causing parts of the system to fail. Stochasticity can be used for different events and expected value of the cost optimized. Another alternative could be, to run a simulation model, which has to be compatible with optimization techniques.

3.3.2 Vulnerability of Interdependent Infrastructure Systems as Combo-Models

The combo-model formulation and implementation in Pyomo supports similar analysis to those defined by Alderson et al. (2014). A combo-model has a combined objective representing the functioning of multiple infrastructure systems. Here, the same methods apply, as the choice of binary variables or stochastic losses for worst-case failures across multiple systems can be from the same or separate sets. In contrast, the final operations of both systems is dictated by two networks with interdependent flows, such that the results for a worst-case interdiction can change.

For example, the choice of two arcs (i.e., attacker budget = 2) that cause a worst-case interdiction in a single network may be entirely different for interdependent system. In the interdependent setting, if the original network is a DM, worst-case interdictions may identify arcs in the SM that decrease network function even more. If both systems are dependent on each other, worst-case interdictions can be found that attack both networks. One important avenue of research is testing the effects of these interdependencies and comparing them to previous understandings of network vulnerabilities.

3.4 Analysis

We conduct a series of analyses for interdependent infrastructure systems to demonstrate the efficacy and capabilities of the combo-model formulation and generator function. First, we analyze the function of interdependent fuel and electric power system models that were previously studied in the literature with other model formulations. We implement the models as a combo-model to show that similarities in results with the added benefit of not needing to define interdependencies in initial model construction.

Then, we use the combo-model formulation and function to easily develop new interdependent infrastructure models and assess their function and vulnerability. Specifically, we implement a transportation model developed by Good (2019) and Routley (2020) that determines traffic flows and travel times for communities on islands to access critical supplies.

This model was used by Routley (2020) to assess transportation on the island of St. Thomas, and not created for interdependent analysis. We connect the St. Thomas model to a fuel and electric power system model using our combo-model approach to assess the effects of electric power system and fuel network failures on the routing of people to access critical supplies.

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CHAPTER 4: Interdependent Energy Networks

We analyze interdependent energy networks to demonstrate the combo-model approach. We present network flow optimization models for a fuel network, an electric power network, and their interdependencies. We demonstrate the use of the combo-model method to construct and analyze a small interdependent system with three nodes in each network. We further demonstrate this approach with a larger interdependent fuel and electric power networks previously studied in Dixon (2011), Dickenson (2014), Ruether (2015), and Alderson et al. (2015). Due to the significant analysis already completed with these models, we only present new results developed using methods in this thesis. We refer the reader to these past studies for additional discussion of network data and analysis.

4.1 Combo-Model Applied to Energy Networks

Previous network flow models for interdependent fuel and electric power systems were formulated with interdependencies known in initial model construction (Dickenson 2014; Ruether 2015). In contrast, we reformulated standalone network flow models for each system, based on the already constructed models, then use the combo-model approach to link models together. In this section, we present each standalone model and the resulting interdependent formulation using our combo-model generator function.

4.1.1 Fuel Network Model

We adapt a fuel network from Dickenson (2014), Ruether (2015), and Alderson et al. (2015) with modification.

Indices and Sets

FN	nodes
$FArcs \subseteq FN \times FN$	arcs

Parameters [units]

$FSupply_i$	fuel supply(+) or demand(-) at node $i \in FN$ [bbl]

$FLdSCost_i$	load shed cost for not fulfilled demand at node $i \in FN$ [$/bbl]
$FArcCost_{(i,j)}$	fuel arc cost on arc $(i, j) \in FArcs$ [$/bbl]
$FArcCap_{(i,j)}$	fuel capacity on arc $(i, j) \in FArcs$ [bbl]
$FArcX_{(i,j)}$	1 if fuel arc $(i, j) \in FArcs$ damaged, 0 otherwise [binary]
$FArcPenCost_{(i,j)}$	damaged arc penalty cost [$/bbl]

Decision Variables [units]

$FY_{(i,j)}$	fuel flow on arc $(i, j) \in FArcs$ [bbl]
$FLdS_i$	load shed (not fulfilled demand) at node $i \in FN$ [bbl]

Formulation

$$\min_{FY,FLdS} \sum_{(i,j)\in FArcs} FArcCost_{(i,j)} \cdot FY_{(i,j)} + \sum_{i\in FN} FLdSCost_i \cdot FLdS_i + \sum_{(i,j)\in FArcs} FArcPenCost_{(i,j)} \cdot FArcX_{(i,j)} \cdot FY_{(i,j)} \tag{4.1}$$

$$\text{s.t.} \quad \sum_{(n,j)\in FArcs} FY_{(n,j)} - \sum_{(i,n)\in FArcs} FY_{(i,n)} - FLdS_n \leq FSupply_n \forall n \in FN \tag{4.2}$$

$$0 \leq FY_{(i,j)} \leq FArcCap_{(i,j)} \qquad \forall (i, j) \in FArcs \tag{4.3}$$

$$FLdS_i = 0 \quad \text{if } FSupply_i \geq 0 \qquad \forall i \in FN \tag{4.4}$$

$$0 \leq FLdS_i \leq -FSupply_i \quad \text{if } FSupply_i < 0 \qquad \forall i \in FN \tag{4.5}$$

Discussion

The model consists of nodes FN and arcs $FArcs$ defining the fuel network. The network consists of supply and demand nodes defined by the parameter $FSupply$. The decision variables define the flow of fuel over each arc ($FY_{(i,j)}$) and the load unserved at demand nodes ($FLdS_i$). The objective (4.1) to minimize the cost of delivering fuel and penalty costs for not meeting demands. Constraint (4.2) defines the flow balance constraints with constraint (4.3) setting the upper and lower bounds on fuel flow over any network arc.

Constraints (4.4) and (4.5) determine unserved demand and penalty costs. Many of the physical properties of real fuel systems (e.g., pressure, transients, etc.) are ignored in this model to keep it as simple as possible while capturing key system function of fuel delivery.

To penalize not fulfilling demand at a node in parts or completely, the decision variable $FLdS_i$ measures the amount of demand shed and the associated parameter $FLdSCost_i$ assigns a penalty cost for each barrel not fulfilled. Moreover, the parameter $FArcPenCost_{(i,j)}$ adds an additional penalty cost for each barrel of fuel transported on a broken arc.

4.1.2 Electric Power Network Model

We link our fuel network to an electric power network to study energy interdependencies. We use a Direct Current Optimal Power Flow (DCOPF) model developed for electric power transmission systems adapted from Dickenson (2014) and Ruether (2015) with modification.

Indices and Sets

PN	nodes
$PNG \subseteq PN$	generator nodes
$PND \subseteq PN$	demand nodes
$PNB \subseteq PN$	bus nodes
$PArcs \subseteq PN \times PN$	arcs
$PEdges \subseteq PN \times PN$	undirected edges

Parameters [units]

$PGenCap_i$	power generator capacity at node $i \in PNG$ [MW]
$PGenCost_i$	power generator cost at node $i \in PNG$ [\$/MW]
$PDem_i$	power demand at node $i \in PND$ [MW]
$PLdSCost_i$	load shed cost for not fulfilled demand at node $i \in PND$ [\$/MW]
$PArcCap_{(i,j)}$	power arc capacity on arc $(i, j) \in PArcs$ [MW]
$PArcRes_{(i,j)}$	power arc resistance on arc $(i, j) \in PArcs$ [Ω]
$PArcRea_{(i,j)}$	power arc reactance on arc $(i, j) \in PArcs$ [Ω]

Calculated Parameters [units]

$PArcSus_{(i,j)}$	power arc susceptance on arc $(i,j) \in PArcs$ [Ω] $PArcSus_{(i,j)} = \frac{PArcRea(i,j)}{PArcRea(i,j)^2 + PArcRes(i,j)^2}$

Decision Variables [units]

$PY_{(i,j)}$	power flow on arc $(i,j) \in PArcs$ [MW]
θ_i	phase angle at node $i \in PN$
$PGen_i$	power generation at node $i \in PNG$ [MW]
$PLdS_i$	load shed (not fulfilled demand) at node $i \in PND$ [MW]

Formulation

$$\min_{PY,PGen,PLdS} \sum_{i \in PNG} PGenCost_i \cdot PGen_i + \sum_{i \in PND} PLdSCost_i \cdot PLdS_i \tag{4.6}$$

$$\text{s.t.} \quad PY_{(i,j)} = PArcSus_{(i,j)} \cdot (\theta_j - \theta_i) \qquad \forall (i,j) \in PEdges \tag{4.7}$$

$$\sum_{(i,n) \in PArcs} PY_{(i,n)} - \sum_{(n,j) \in PArcs} PY_{(n,j)} = 0 \qquad \forall n \in PNB \tag{4.8}$$

$$PGen_n + \sum_{(i,n) \in PArcs} PY_{(i,n)} - \sum_{(n,j) \in PArcs} PY_{(n,j)} = 0 \qquad \forall n \in PNG \tag{4.9}$$

$$\sum_{(i,n) \in PArcs} PY_{(i,n)} - \sum_{(n,j) \in PArcs} PY_{(n,j)} + PLdS_n = PDem_n \qquad \forall n \in PND \tag{4.10}$$

$$PY_{(i,j)} - PY_{(j,i)} = 0 \qquad \forall (i,j) \in PEdges \tag{4.11}$$

$$PY_{(i,j)} \leq PArcCap_{(i,j)} \qquad \forall (i,j) \in PArcs \tag{4.12}$$

$$0 \leq PGen_i \leq PGenCap_i \qquad \forall i \in PNG \tag{4.13}$$

$$0 \leq PLdS_i \leq PDem_i \qquad \forall i \in PND \tag{4.14}$$

Discussion

The electric power network consists of nodes (PN) and arcs ($PArcs$), where there are different types of nodes: Generator: PNG, Demand: PND, and Bus: PNB. Bus-nodes span the network, where generator nodes produce electricity and demand nodes require electricity. To include the physical property of phase angles in an electric power network, edges $PEdges$ are used as an undirected arc ($PArcs$).

The supply in the electric power network is modeled at generator nodes PNG, with a maximum capacity $PGenCap_i$ and an assigned cost for each generated megawatt (MW) ($PGenCost_i$), where the cost is set to the cost of a megawatt-hour (MWh). The actual produced electric power by this generator node is the decision variable $PGen_i$. On the other end of the power flow is the demand, which is set by parameter $PDem_i$. Same as in the fuel network, unserved demand is considered as shed load, modeled by the decision variable $PLdS_i$ and the corresponding cost parameter $PLdSCost_i$ for each unit (MW) of not delivered. The capacity of each arc representing a power line is set by $PArcCap_{(i,j)}$.

The physical properties of DCOPF are determined by the power line parameters resistance ($PArcRes_{(i,j)}$) and reactance ($PArcRea_{(i,j)}$). These parameters are used to calculate power line susceptance ($PArcSus_{(i,j)}$) with the following formula:

$$PArcSus_{(i,j)} = \frac{PArcRea(i,j)}{PArcRea(i,j)^2 + PArcRes(i,j)^2}$$

In addition to these three parameters, the decision variable θ_i is used for the phase angle at a node to calculate the power balance in the network.

The network flow optimization is controlled by minimizing the objective function (4.6), which is the sum of the power generation cost at the power generators and the penalty cost for shedding load (not fulfilling demand). Constraint (4.7) maintains the physical properties of the electric power grid and the flow in the network. Constraints (4.8), (4.9) and (4.10) keep the three types of nodes in balance and adjust the needed generation energy ($PGen_i$) and the shed load ($PLdS_i$). The constraint (4.11) is used to balance the two arcs, which are forming an edge. Constraint (4.12) is to keep the flow on an arc within its capacity limit and the last two constraints (4.13) and (4.14) are the non-negativity constraints for the decision variables ($PGenCap_i$) and ($PDem_i$).

There is one key difference between the electric power model formulation presented here and and the models developed in Dickenson (2014) and Ruether (2015). Past work included variables, parameters, and constraints for interdependent fuel and electric power flows in the model formulation. We remove these constraints since the combo-model approach develops them without the need of defining them in the initial model. The rest of the model is as is.

4.1.3 Energy Combo-Model

Fuel and electric power systems are interdependent on each other for network function. In this work, we consider two dependencies — one from the electric power system on fuel, and one from the fuel system on electricity. We model a dependency of the electric power network (i.e., DM) on the fuel network (i.e., SM) via the delivery of fuel through the fuel network generator nodes in the electric power network for power generation. This is a node-node dependency, where fuel commodities flow to nodes in the fuel network and serve generator nodes in the electric power network.

Figure 4.1 shows the use of the combo-model generator function to easily create this node-node dependency with the models presented above as Pyomo model objects. The model of the fuel network is input to the function as *model1* and the model of the electric power network is *model2*. We use the combo-model generator function to create a one-way dependency model from electric power to fuel and save it to a file entitled power_on_fuel.py. Decision variables governing the delivery of fuel to electric power generators are FY which is defined for flow over arcs $FArcs$. The dependent nodes are a subset of $PGen$, where fuel delivery controls the capacity of generation $PGenCap$ at a given node. The resulting file is a Pyomo model object with a built in method for populating these dependencies for testing different sets of interdependent electric power and fuel nodes and defining different functional thresholds for fuel delivery to allow generation.

```
COMBO-MODEL-GENERATOR
=====================
Name for generated file (.py): power_on_fuel.py
#####
How many dependencies? (1-4): 1
#####
Dependency 1:
Directions: model1(2) depends on model2(1) --> 1on2 (2on1)
Enter the direction of the dependency: 2on1
Types: node-on-node: nn / node-on-arc: na / arc-on-node: an / arc-on-arc: aa
Enter the type of the dependency: nn
Flow variable and arcs of model1:
Var of model1:
['FY', 'FLdS']
Enter the flow variable of model1: FY
Set of model1:
['FN', 'FArcs_domain', 'FArcs']
Enter the arc set where the flow is on of model1: FArcs
Dependent element (generating node / flow variable of arc) and capacity of model2:
Var of model2:
['PY', 'theta', 'PGen', 'PLdS']
Enter the dependent generating node / flow variable of model2: PGen
Param of model2:
['PGenCap', 'PGenCost', 'PDem', 'PLdSCost', 'PArcCap', 'PArcRes', 'PArcRea', 'PArcSus']
Enter the dependent node/arcs capacity of model2: PGenCap
#####
```

Figure 4.1. Combo-Model Generator Function Applied to Energy Networks. The combo-model generator function presented in Ch. 3 is used to create an interdependent fuel and electric power network. Here, we are generating a combo-model object with a node-to-node dependency for an electric power generator that requires fuel to function. User-input is underlined in red.

We also consider a dependency of the fuel network on electricity to operate pumps that enable the flow of fuel. This is an arc-node dependency, where power demand nodes supply electricity to fuel pumps modeled as arcs. This can be included as a second dependency when generating a combo model, very similar steps to those shown in Figure 4.1. This generates an interdependent infrastructure model where the function of fuel and electric power networks depend on each other and are solved simultaneously.

The combo-model approach generates a network flow model that adds the following modifications and additions to the standalone fuel and electric power networks, which are very similar to these, used in Dickenson (2014) and Ruether (2015), only with generic names.

Indices and Sets

$PDFA \subseteq FArcs$	electric power consuming fuel arc
$FDPN \subseteq PNG$	fuel consuming electric power node

Parameters [units]

$PThresh_{(i,j)}$	power needed at fuel arc $(i, j) \in PDFA$ [MW]
$PPN_{(i,j)} \in PND$	power providing node at fuel arc $(i, j) \in PDFA$
$FThresh_i$	fuel needed at power node $i \in FDPN$ [bbl]
$FPN_i \in FN$	fuel providing node at power node $i \in FDPN$

Decision Variables [units]

$TFuel_{(i,j)}$	1 if fuel transported by arc $(i, j) \in PDFA$, 0 otherwise [binary]
$TPower_i$	1 if electric power produced by node $i \in FDPN$, 0 otherwise [binary]

Formulation

$$\min_{PY,PGen,PLdS,FY,FLdS} \quad \sum_{i \in PNG} PGenCost_i \cdot PGen_i + \sum_{i \in PND} PLdSCost_i \cdot PLdS_i + \sum_{(i,j) \in FArcs} FArcCost_{(i,j)} \cdot FY_{(i,j)} + \sum_{i \in FN} FLdSCost_i \cdot FLdS_i + \sum_{(i,j) \in FArcs} FArcPenCost_{(i,j)} \cdot FArcX_{(i,j)} \cdot FY_{(i,j)} \tag{4.15}$$

$$
\begin{aligned}
\text{s.t.}\quad & (4.2), (4.3), (4.4), (4.5), (4.7), (4.8), \\
& (4.9), (4.10), (4.11), (4.12), (4.13), (4.14) \\
& PThresh_{(i,j)} \cdot TFuel_{(i,j)} \leq \sum_{(k,PPN_{(i,j)}) \in PArcs} PY_{(k,PPN_{(i,j)})} \\
& \qquad - \sum_{(PPN_{(i,j)},m) \in PArcs} PY_{(PPN_{(i,j)},m)} && \forall (i,j) \in PDFA \quad (4.16) \\
& 0 \leq FY_{(i,j)} \leq FArcCap_{(i,j)} \cdot TFuel_{(i,j)} && \forall (i,j) \in PDFA \quad (4.17) \\
& TFuel_{(i,j)} \in \{0,1\} && \forall (i,j) \in PDFA \quad (4.18) \\
& FThresh_n \cdot TPower_n \leq \sum_{(i,FPN_n) \in FArcs} FY_{(i,FPN_n)} \\
& \qquad - \sum_{(FPN_n,j) \in FArcs} FY_{(FPN_n,j)} && \forall n \in FDPN \quad (4.19) \\
& 0 \leq PGen_n \leq PGenCap_n \cdot TPower_n && \forall n \in FDPN \quad (4.20) \\
& TPower_n \in \{0,1\} && \forall n \in FDPN \quad (4.21)
\end{aligned}
$$

Discussion

This combo-model formulation combines elements from standalone fuel and electric power networks. All indices, sets, parameters, decision variables, and constraints are retained from both models. For the purposes of space, we do not reproduce these model elements in the combo-model formulation.

The needed indices, sets, parameters, decision variables, and constraints for interdependent function are now added again in the combined model with the two sub-models. Sets for power generator nodes that depend on fuel ($FDPN$) and fuel arcs that depend on electricity ($PDFA$) are added to the model. The fuel required for electric power generators to work is the parameter $FThresh_i$, where the serving fuel node provides fuel FPN_i. Similarly, fuel arcs requiring electricity for pumping are assigned a parameter $PThresh_{(i,j)}$, with serving electric power demand nodes $PPN_{(i,j)}$. Both dependencies are modeled binary, so that the dependent nodes are only working if the specific threshold of commodity is reached. While these are produced from standalone models and the combo-model generator function, they are identical to the model elements used by Dickenson (2014) and Ruether (2015) to consider energy network dependencies.

The objective function for the combo-model is an unweighted, linear combination of the fuel network and electric power network objectives. The overall objective is to minimize both transportation cost of all commodities and any costs incurred for load shed.

The first three constraints (4.16 - 4.18) model fuel arcs that depend on electricity, Constraint (4.16) set the decision variable $TFuel_{(i,j)}$ as a switch determining if $PThresh_{(i,j)}$ is met by the $PPN_{(i,j)}$. Constraint (4.17) activates the fuel arc (i, j), if $TFuel_{(i,j)} = 1$ and (4.18) defines $TFuel_{(i,j)}$ to be binary.

The next three constraints (4.19 - 4.21) model electric power generators dependent on fuel. Constraint (4.19) $TPower_i$ switches to 1 if $FThresh_i$ is met by the serving fuel node FPN_i in the fuel network. Constraint (4.20) activates the power generating node if $TPower_i = 1$ and (4.21) defines $TPower_i$ to be binary.

Overall, the combo-model formulation captures the key dependencies across both energy networks for interdependent analysis. The resulting model formulation has an objective and constraints that relate networks together such that their flows depend on their interdependent function. This approach has more flexibility for studying dependencies and interdependencies than others found in the literature by decoupling functional thresholds from flow demands. Importantly, prior knowledge of fuel and electric power dependencies is not required when constructing initial fuel and electric power networks. The simplicity of this approach lends itself to easily studying the function of multiple interdependent systems.

4.2 Interdependent Energy Network Analysis

We analyze the function and vulnerability of interdependent fuel and electric power networks generated using the combo-model approach to demonstrate its use. We analyze two interdependent systems:

1. A simple fuel and electric power network consisting of three nodes; and.

2. A realistic fuel and electric power network using data from Dickenson (2014) and Ruether (2015).

Each analysis serves a different purpose. The first, simple analysis demonstrates the output of an interdependent energy network. The second, realistic analysis demonstrates that the combo-model formulation produces equivalent results to past studies. Together, these analyses demonstrate model output and validate the combo-model approach.

4.2.1 Simple Fuel and Electric Power Networks

We present a very simple interdependent energy network to demonstrate analysis. The simple interdependent model consists of a small fuel and electric power network. The simple fuel network consists of three nodes. Figure 4.2 visualizes the network and shows model output minimizing fuel delivery costs as a standalone system:

- **FN1sup (blue):** Supply node, can supply up to 200 bbl of fuel and is connected to FN2 (red).
- **FN2 (red):** Demand node, has demand of 100 bbl of fuel and is connected to FN1sup (blue) and FN3 (orange).
- **FN3 (orange):** Demand node, has demand of 100 bbl of fuel and is connected to FN2 (red).

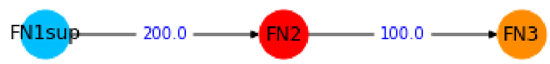

Figure 4.2. Simple Fuel Network. FN1sup (blue) is a supply node with capacity 200 Barrel (bbl), FN2 (red) and FN3 (orange) are demand nodes, each with a demand of 100 bbl. Flow over fuel arcs travels from FN1Sup to FN2 to FN3. This is the minimum cost flow for this network as a standalone system.

The simple electric power network consists of 4 nodes. Figure 4.3 visualizes the network and shows model output minimizing electric power delivery costs as a standalone system:

- **2 power generators (blue):** gf1, a fuel fired power generator and gs1, a small turbine generator. They have each a capacity of 100 MW and have a different production cost assigned, where gf1 is cheaper than gs1. Both are connected to the bus node i1.
- **1 bus node (green):** Bus node i1 is connected to all three components.
- **1 demand node (orange):** Demand nod dn1 has a power demand of 70 MW of electric power and is connected to i1.

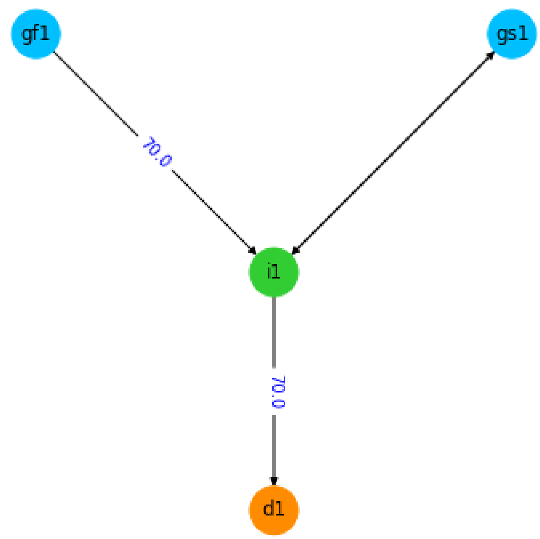

Figure 4.3. Simple Electric Power Network. The network has two generators, gf1 (fuel powered) and gs1 (small generator), each able to generate 100 MW of electric power (blue). Each generator has a different cost, where gs1 produces cheaper electric power than gs1. Bus node i1 (green) connects generators to demand node d1 (orange), which requires 70 MW of electric power.

Interdependent Network Flow Analysis

Both models are interdependent on each other. The simple fuel network depends on electric power to transport fuel from FN2 to FN3. This represents a pump on this arc (arc-node dependency), which is only working, if there is at least 60 MW available at d1. The simple electric power network is dependent on fuel from the fuel node FN3 to generate electricity at gf1 (node-node dependency). The required threshold for it to work is 80 bbl. Thus, the minimum cost delivery of fuel and electric power for both systems remains the same to the standalone networks. Figures 4.2 and 4.3 show dependent elements in orange.

We analyze the vulnerability of a single fuel arc failure on the interdependent function of each simple network. We assume that the pipe (arc) between FN2 and FN3 in the fuel network fails and cannot be used. The resulting flows in the fuel network are shown in Figure 4.4. The failure of this arc results in electric power generator gf1 not being able to function. Instead, gs1, which is more expensive to use, has to fulfill electric power demand.

Resulting power flow is shown in Figure 4.5.

Figure 4.4. Simple Fuel Network with Arc Failure and Interdependent Solve. Pipe (FN2, FN3) is assumed to be broken, so no flow possible. This restricts the function of power generators in the simple electric power network that require fuel to function.

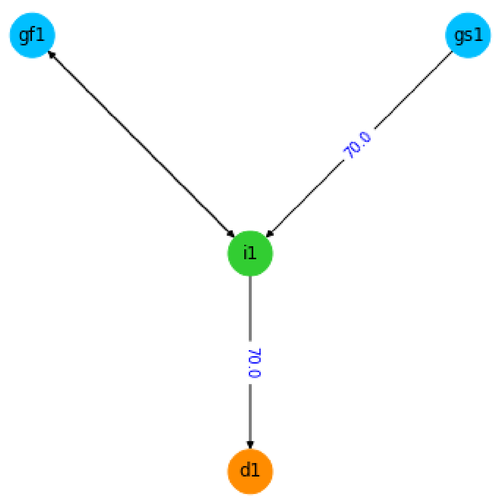

Figure 4.5. Simple Electric Power Network with Fuel Arc Failure and Interdependent Solve. Fuel-powered generator gf1 is dependent on fuel from FN3 in the simple fuel network. Due to an arc failure in the fuel network gf1 is not able to produce electric power. Instead, gs1 produces electric power at a higher cost to serve demand.

Tables 4.1 and 4.2 show the changes in network flow costs and effects of dropped demand caused by the interdependent failure. The broken fuel arc results in a higher objective value for both systems, where the combination of dropped demand and unserved nodes in the fuel network causes its objective to become 150 times greater. This is because each bbl of fuel costs 150, which results in the increase of this value by $15,000$.

The electric power network objective only increases by 100% as increased costs are incurred for the new generation source but there is no dropped demand. However, this increase in cost could not be captured without the inclusion of networked interdependencies. Together, the interdependent vulnerability of both networks is measured using the combo-model approach.

Table 4.1. Objective Values in Simple Interdependent Energy Network.

Scenario	**Fuel**	**Electric Power**
No Failure	100.02	700.00
Fuel Arc Broken	15,000.01	1,400.00

Table 4.2. Dropped Demand in Simple Interdependent Energy Network.

Scenario	**Fuel**	**Electric Power**
No Failure	0	0
Fuel Arc Broken	100	0

4.2.2 Realistic Fuel and Electric Power Networks

We analyze a larger fuel and electric power network to validate the combo-model approach against past studies.

The realistic fuel network is a 16-node system first introduced in Dickenson (2014) and Ruether (2015) and studied in detail in Alderson et al. (2015). Figure 4.6 presents the supply and demand nodes, their networked structure via pipeline arcs for fuel delivery, and the flows for solving the min cost fuel model using this network. The network consists of two supply nodes (blue) with each a capacity of 1350 bbl and 14 demand nodes (i.e., all red or orange nodes except FN10 and FN8). The demand nodes have each different demands and the orange nodes are the nodes, where elements of the electric power network are dependent on. All additional data for the fuel network, including fuel supply limits, arc capacities, flow costs, and demand requirements, are the same as the network presented in Dickenson (2014) andRuether (2015). We refer the reader to these previous studies for detailed information on network parameters.

We also adapt a realistic electric power network from Dickenson (2014) and Ruether (2015). The electric power network is shown in Figure 4.7. It consists of 33 electric power generators of different types (fuel, nuclear, hydroelectric and coal) and for each type they have a different production cost. Electric power is delivered via a network of 24 bus nodes to 17 demand nodes, each with a different amount of demand. There are also 4 additional bus nodes ending with the letter "p", which are fake nodes to enable parallel power lines.

Figure 4.7 also shows the results for solving the DCOPF model for this network as directed the flow of electricity over arcs. All additional data for the network model, including electric power supply limits, arc capacities, flow costs, and demand requirements, are the same as the network presented in Dickenson (2014) and Ruether (2015). We refer the reader to these previous studies for detailed information on network parameters.

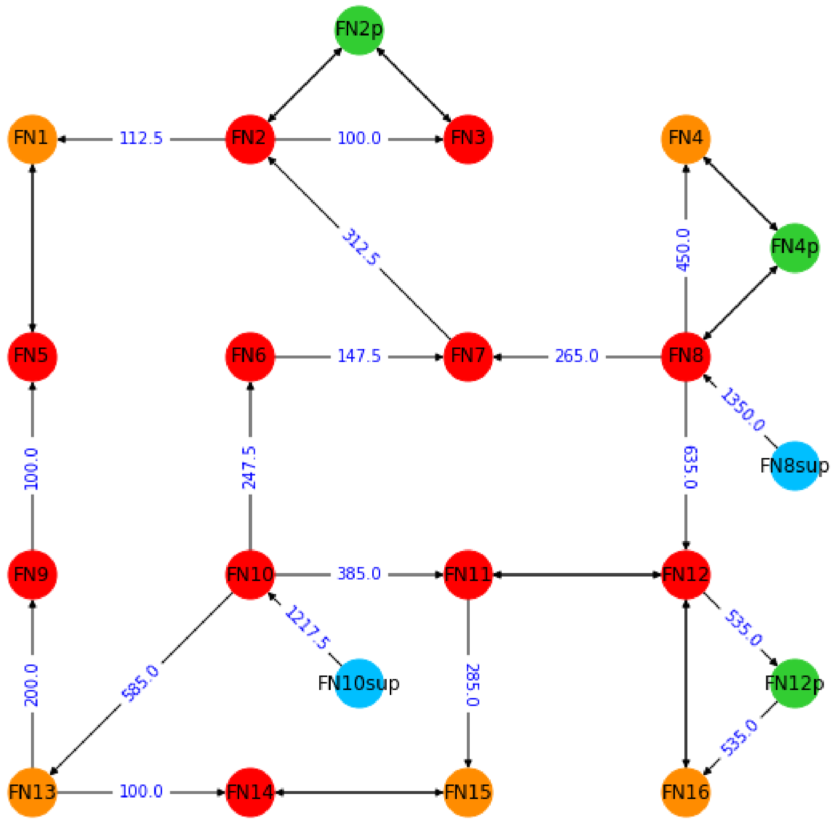

Figure 4.6. Realistic Fuel Network. The fuel network connects supply nodes (blue), demand nodes (red and orange), and fictitious nodes for modeling parallel pipes (green) via pipes represented as arcs. Orange nodes indicate locations where the fuel network serves fuel to the realistic electric power network. The data for this network can be used to solve the min cost fuel problem with and without interdependencies. The results for solving this problem without interdependencies is shown on arcs in bbl. Network data and figure based on Ruether (2015).

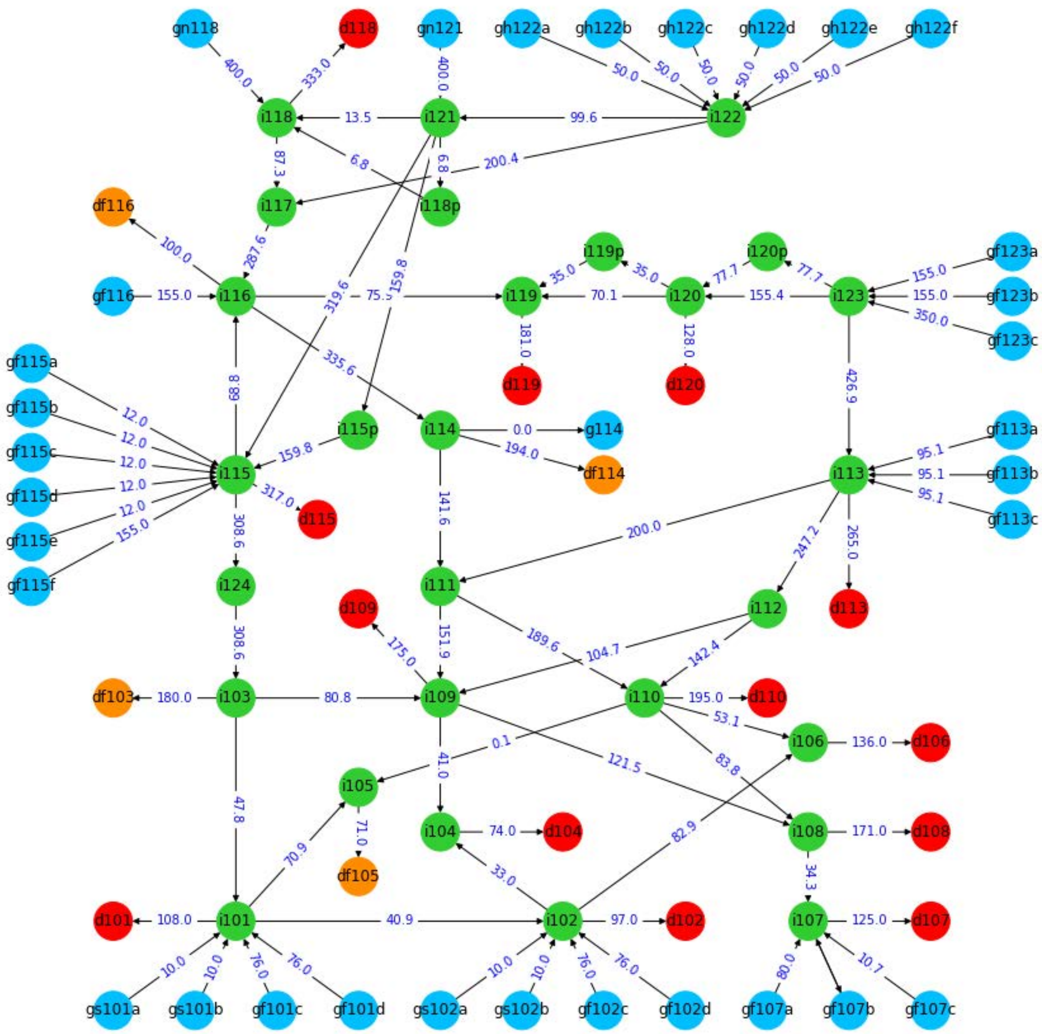

Figure 4.7. Realistic Electric Power Network. The electric power network delivers electricity from power generator nodes (blue) to demand nodes (red and orange) via intermediate bus nodes (green). Orange nodes indicate locations where the electric power network serves electricity to the realistic fuel network. The data for the network supports solving a min cost DCOPF problem with and without interdependencies. The results for solving this problem without interdependencies is shown on power lines in MW. Network data and figure based on Ruether (2015).

Interdependent Network Flow Analysis

We use our combo-model approach to connect the realistic fuel and electric power networks for interdependent analysis. The fuel network serves electric power generators and electric power network serves fuel pumps. Interdependencies are located at orange nodes in Figure 4.6 and Figure 4.7. During normal system function, network flows remain the same as in the standalone cases.

We compare results from combo-model flows with past results from Ruether (2015). Table 4.3 shows the comparison of objective value results with past studies and the combo-model methods. As values are the same, we verify that the combo-model formulation and associate generator function produce acceptable results.

Table 4.3. Comparison of Combo-Model Objective Value with Ruether (2015). He analyzed the interdependent function of both realistic energy networks and published results for their respective objective values. The combo-model and generator function approach produces identical results to previous studies verifying its use for interdependent infrastructure analysis.

Results	**Fuel**	**Electric Power**
Ruether (2015)	4,460.26	84,900.80
Combo-Model	4,460.26	84,900.80

We test the vulnerability of the interdependent system with a single power line arc failure between bus node i105 and df105. This node supplies electricity to pumps for fuel supply node FN10sup and the network. This loss of fuel supply causes load shed in the fuel network shutting down fuel driven electric power generators gf102c, gf102d, and gf115a-gf115e. This loss causes a re-balancing of the electric power network to adapt to the loss of production capacity. Resulting interdependent flows are shown in Figures 4.8 and 4.9.

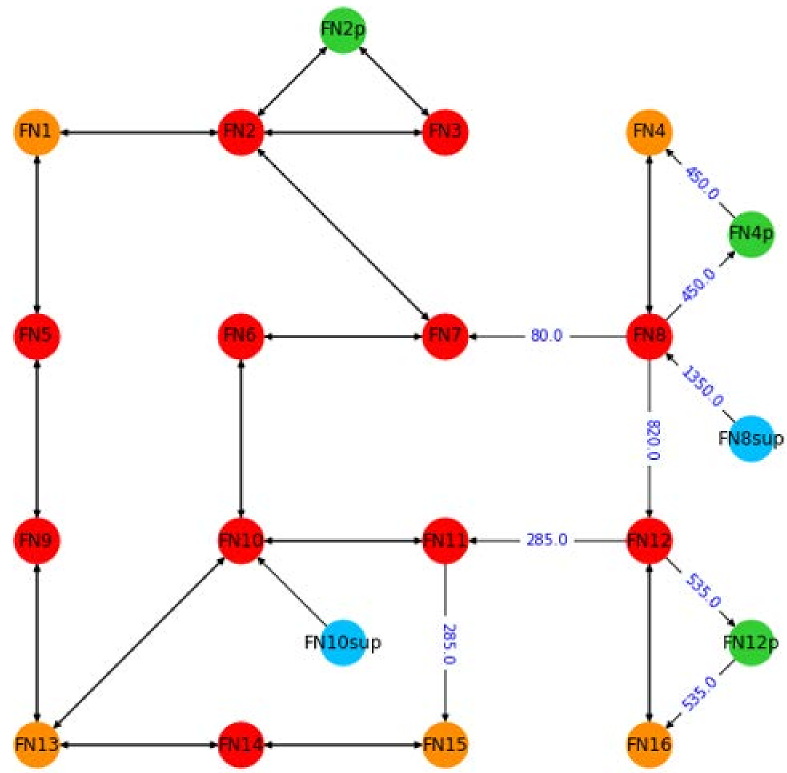

Figure 4.8. Realistic Fuel Network with Arc Failure and Interdependent Solve. Power line (i105, df105) is assumed to be broken, shutting down pumps from FN10sup to the fuel network and leading to dropped demand across the network. Several orange nodes supplying fuel to the electric power network are unable to.

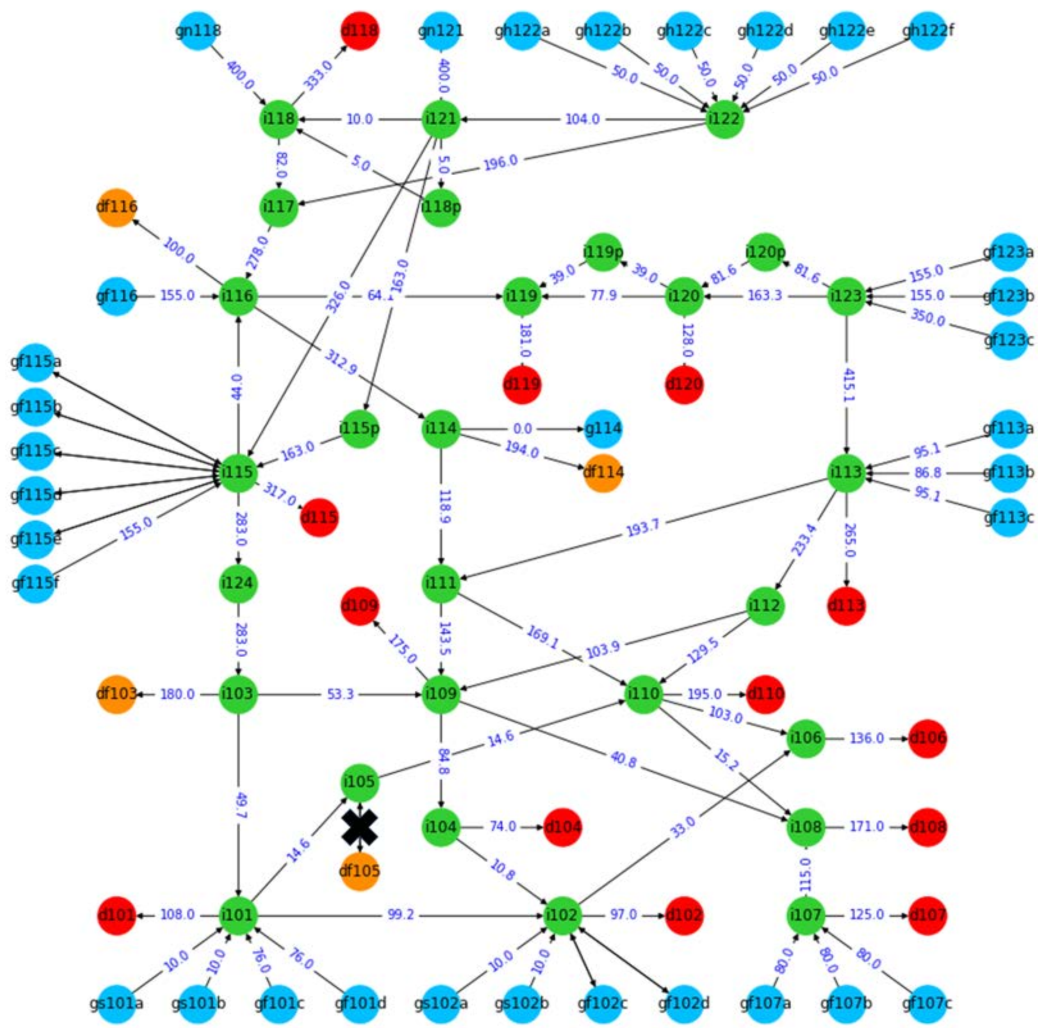

Figure 4.9. Realistic Electric Power Network with Arc Failure and Interdependent Solve. Power line (i105, df105) is assumed to broken, shutting down pumps from FN10sup to the fuel network and leading to dropped demand across the network. Several generators are unable to produce electricity due to loss of fuel. All demand remains served as lost fuel-powered generation is replaced with more expensive generators.

We compare the effects of interdependencies on network operations (Table 4.4 and 4.5). A single power line failure results in a significant portion of the fuel network losing access to fuel, including several demand nodes serving fuel to the electric power network. A total of 1,217.5 bbl of fuel becomes dropped demand and the resulting objective value for the network increases over 40 times. Still, the electric power network has enough capacity to fulfill the demand after losing access to 7 generators, leading to a minor increase in objective value and no dropped demand. Since the initial failure was in the electric power network, the dropped demand in the fuel network and increased generation costs and power dispatch are only captured due to interdependent analysis.

Table 4.4. Objective Values in Realistic Interdependent Energy Network.

Scenario	**Fuel**	**Electric Power**
No Failure	4,460.26	84,900.80
Power Arc Broken	185,080.14	87,679.74

Table 4.5. Dropped Demand in Realistic Interdependent Energy Network.

Scenario	**Fuel**	**Electric Power**
No Failure	0	0
Power Arc Broken	1,217.5	0

4.3 Summary

Analysis of interdependent energy networks demonstrates the application of the approach of the combo-model generator function. We implement previously studied fuel and electric power networks and use the combo-model generator function to create an interdependent model. We test our approach using simple and realistic networks. Results validate the combo-model approach and show the importance of interdependent vulnerability analysis. In the next chapter, we expand this analysis to include network models never created for interdependent analysis.

CHAPTER 5:
Interdependent Energy and Transportation Networks

In the previous chapter, we show that the combo-model methods are extensible to multiple energy models and networks. While the combo-model approach simplified model development, the realistic energy networks were already validated for interdependent analysis in past studies. In this chapter, we demonstrate the use of the combo-model approach for interdependent analysis with a network flow model not originally created for interdependency analysis. Specifically, we study dependencies and interdependencies across fuel, electric power, and transportation networks.

5.1 Combo-Model Applied to Energy and Transportation Networks

We study energy and transportation dependencies using network models from Ch. 4 and a transportation model developed by Good (2019) and Routley (2020). The transportation model measures the capacity of a transportation network to support access to critical supplies during a set curfew period. The purpose of the model is to determine the best routing for communities on an island to access disaster supplies given possible disruptions to the transportation network. The model is validated for use with data from the islands of St. Thomas, St. John, and St. Croix in the USVI.

5.1.1 Transportation Network

We adapt the roadway transportation and supply chain network developed by Good (2019) and Routley (2020) for interdependent infrastructure analysis. The formulation reproduced here is the same from Routley (2020).

Indices and Sets

$i \in N$	nodes (alias j, s, t)
$(i, j) \in A \subseteq N \times N$	arcs
$(s, t) \in D \subseteq N \times N$	set of all origin and destination pairs

$r \in R$ — sections for piece-wise linear approximation
($\bar{r}$ = total number of sections)

$Out_i \subset A$ — set of all outbound arcs from node i

$In_i \subset A$ — set of all inbound arcs to node i

Data [units]

b_{st} — supply rate at node s destined for node t
($b_{st} < 0$ represents demand) [vehicles per hour (VPH)]

u_{ij} — nominal capacity of arc (i, j) [VPH]

s_{ij} — unrestricted speed of arc (i, j) [miles per hour (MPH)]

d_{ij} — length of arc (i, j) [miles]

$avail_{ij}$ — 1 if arc (i, j) is available for use, 0 otherwise

q — maximum intended travel window for all
origin-destination roundtrips [hours]

Calculated Data [units]

λ_{ij} — interval width on arc (i, j) for calculating piecewise linear congestion
$\lambda_{ij} = 2u_{ij}/\bar{r}$

h_{ijr} — total travel time for all vehicles traversing segment r on arc (i, j)
$h_{ijr} = \left(r\lambda_{ij}\right)\left(\frac{d_{ij}}{s_{ij}}\right)\left(1 + 0.15\left(\frac{r\lambda_{ij}}{u_{ij}}\right)^4\right)$

$slope_{ijr}$ — slope of segment r for arc (i, j)
$slope_{ijr} = \frac{h_{ijr} - h_{ijr-1}}{\lambda_{ij}}$

$intercept_{ijr}$ — y intercept of line section r for arc (i, j)
$intercept_{ijr} = -slope_{ijr}(r\lambda_{ij}) + h_{ijr-1}$

Decision Variables [units]

Y_{stij} — flow rate of supply originating at node s destined for node t
transiting arc (i, j) [VPH]

Y_{ij} — total flow rate transiting arc (i, j) [VPH]

Z_{ij} — travel time on arc (i, j) [vehicle hours]

$Dropped_{st}$ — dropped quantity of supply originating at node s destined for node t [vehicles]

$Excess_{st}$ excess quantity of demand originating at node s destined for node t [vehicles]

Formulation

$$\min_{Y,Z,Dropped,Excess} \quad \sum_{(i,j)\in A} Z_{ij} + \sum_{(s,t)\in D, s\neq t} \frac{q}{2} \cdot Dropped_{st} \tag{5.1}$$

$$\text{s.t.} \quad \sum_{(i,j)\in Out_i} Y_{stij} - \sum_{(j,i)\in In_i} Y_{stji} + Dropped_{st} = b_{st} \quad \forall i \in N, (s,t) \in D, i = s \tag{5.2}$$

$$\sum_{(i,j)\in Out_i} Y_{stij} - \sum_{(j,i)\in In_i} Y_{stji} - Excess_{st} = -b_{st} \quad \forall i \in N, (s,t) \in D, i = t \tag{5.3}$$

$$\sum_{(i,j)\in Out_i} Y_{stij} - \sum_{(j,i)\in In_i} Y_{stji} = 0 \quad \forall i \in N, (s,t) \in D, i \neq s, i \neq t \tag{5.4}$$

$$Y_{stij} \leq b_{st} \quad \forall (s,t) \in D, (i,j) \in A \tag{5.5}$$

$$Y_{ij} = \sum_{s,t\in D} Y_{stij} \quad \forall (i,j) \in A \tag{5.6}$$

$$Y_{ij} \leq 2u_{ij}avail_{ij} \quad \forall (i,j) \in A \tag{5.7}$$

$$Z_{ij} \geq intercept_{ijr} + slope_{ijr} \cdot Y_{ij} \quad \forall (i,j) \in A, \forall r \in R \tag{5.8}$$

$$Excess_{st} = Excess_{ts} \quad \forall (s,t) \in D \tag{5.9}$$

$$Dropped_{st} = Dropped_{ts} \quad \forall (s,t) \in D \tag{5.10}$$

$$Y_{stij}, Y_{ij}, Z_{ij}, Dropped_{st}, Excess_{st} \geq 0 \quad \forall (i,j) \in A, (s,t) \in D \tag{5.11}$$

Discussion

We provide a succinct description of this model for the purposes of interdependent analysis. For more details on the model formulation and use, we refer the reader to Good (2019) and Routley (2020).

The transportation model consists of nodes N and arcs A, with multi-commodity flow on arcs (i, j) originating from a source node s and traveling to a destination node t. The multi-commodity flows capture vehicles that travel from the same origins to different destinations (s, t) and their shared congestion on roads (i, j) driven by a supply rate b_{st}. This formulation also takes into account travel due to a return trips, where any arriving vehicle traveling from s to t generates a return trip from t to s.

The objective function (5.1) minimizes the vehicle-hours drivers spend on roads (Z_{ij}). It identifies the best routes drivers should take for all (s, t) pairs simultaneously. The objective balances the travel time to and from an (s, t) pair with staying at home and not traveling at all. This balance is dictated by parameter q, which sets a maximum travel time window.

Constraints (5.2) to (5.4) enforce balance of flow for all nodes, where decision variables $Dropped_{st}$ and $Excess_{st}$ determine total vehicles unable to travel to their intended destination in the travel time window. Constraint (5.5) sets the supply-demand capacity for each route. The sum of the traffic density on one road arc is computed by constraint (5.6) and the maximum capacity of a road enforced by constraint (5.7). The minimal travel time on an arc is enforced by Constraint (5.8) and the symmetry of elastic variables is set by constraints (5.9) and (5.10). The non-negativity of all decision variables is enforced by Constraints (5.11).

An important aspect of this model is that cycles are possible, where vehicles take routes that incur travel costs smaller than the objective gap. This is possible because short roads may incur very small values of Z_{ij} when the number of vehicles on the road is far from the capacity u_{ij}. Good (2019) introduced a cycle-breaking algorithm to remove any cycles post-optimization solve. Routley (2020) implements the same algorithm, which we also use here.

5.1.2 Transportation and Energy Combo-Models

We link the roadway transportation and supply chain model to fuel and electric power networks developed in Ch. 4. There are many dependencies that can be modeled between energy and transportation networks, including interdependent effects between roads, electric power lines, pipelines, locations of supply, locations of commodity use, and access to assets via the transportation network. We focus our analysis on the delivery of fuel and electricity to locations of commodity use within the roadway network with fictitious examples.

Fuel and Transportation Combo-Models (Gas Stations)

The fuel network supplies fuel via pipeline to gas stations and fuel depots across the roadway transportation network. This dependency is a arc-node dependency affecting the fuel supply destinations in the roadway transportation network, where an inability to deliver fuel leads to the node and associated roads becoming unavailable and to the rerouting of vehicles to access fuel from other locations. Thus, this arc-node dependency involves the activation and deactivation of roadway links representing all entrances and exist from locations of fuel supply in the transportation model.

Using the combo-model approach results with the following formulation.

Indices and Sets

$FDTA \subseteq A$	transportation arcs dependent on fuel

Parameters [units]

$FThresh_{(i,j)}$	fuel needed at road arc $(i, j) \in FDTA$ [bbl]
$FPN_{(i,j)} \in FN$	fuel providing node at road arc $(i, j) \in FDTA$

Decision Variables [units]

$TTrsp_{(i,j)}$	1 if road arc $(i, j) \in FDTA$ available, 0 otherwise [binary]

Formulation

$$\begin{aligned}\min_{FY,FLdS,Y,Z,Dropped,Excess} \quad & \sum_{(i,j)\in FArcs} FArcCost_{(i,j)} \cdot FY_{(i,j)} + \sum_{i\in FN} FLdSCost_i \cdot FLdS_i + \\ & \sum_{(i,j)\in FArcs} FArcPenCost_{(i,j)} \cdot FArcX_{(i,j)} \cdot FY_{(i,j)} + \\ & \sum_{(i,j)\in A} Z_{ij} + \sum_{(s,t)\in D, s\neq t} \frac{q}{2} \cdot Dropped_{st}\end{aligned} \tag{5.12}$$

$$
\begin{aligned}
&\text{s.t.}(4.2) - (4.5), (5.2) - (5.11) && && \\
&\quad FThresh_{(i,j)} \cdot TTrsp_{(i,j)} \leq Y_{(i,j)} && \forall (i,j) \in FDTA && (5.13) \\
&\quad 0 \leq Y_{(i,j)} \leq 2 \cdot u_{(i,j)} \cdot TTrsp_{(i,j)} && \forall (i,j) \in FDTA && (5.14) \\
&\quad TTrsp_{(i,j)} \in \{0,1\} && \forall (i,j) \in FDTA && (5.15)
\end{aligned}
$$

Discussion

The fuel-transport combo-model formulation follows the same form as our generic formulation (Section 4.1.3). It combines elements from standalone transport and fuel networks, which we do not repeat here for the purposes of space.

The combo-model adds a set of transportation arcs dependent on fuel from the fuel model. These arcs are the on-ramp and off-ramp road arcs that drivers must take in the transportation model to access a gas station. The required amount of fuel at the gas station is $FThresh_{(i,j)}$, where the serving fuel node $FPN_{(i,j)}$ is provides fuel to the gas station.

The objective function is an unweighted, linear combination of the transportation network and fuel network objectives. The combined objective is to minimize the transportation cost of the fuel, the vehicle hours on each arc and the dropped demand in the transportation model.

Constraint (5.13) sets the decision variable $TTrsp_{(i,j)}$ as a switch determining if $FThresh_{(i,j)}$ is met by the $FPN_{(i,j)}$. Constraint (5.14) activates the transportation arc (i, j) to and from the gas station i if $TTrsp_{(i,j)} = 1$. This constraint replaces constraint (5.7) in the original transportation model. Constraint (5.15) defines $TTrsp_{(i,j)}$ to be binary. The resulting model leads to rerouting of vehicles to other gas stations if the fuel network, the transportation model is dependent on, does not deliver enough fuel to node i.

Electric Power and Transportation Combo-Models (Traffic Lights)

The electric power network supplies electricity to traffic lights at major intersections in the roadway transportation network. This dependency is similar to the fuel dependency as a node-node connection. However, rather than affecting destinations, it affects transshipment nodes in the transportation network. Whereas loss of fuel at a gas station primarily leads to rerouting of vehicles traveling to gas stations, loss of electricity at an intersection leads to rerouting of all vehicles transiting the intersection for accessing all commodities.

Using the combo-model approach results with the following formulation.

Indices and Sets

$PDTA \subseteq A$	transportation arcs dependent on electricity

Parameters [units]

$PThresh_{(i,j)}$	power needed at road arc $(i, j) \in PDTA$ [bbl]
$PPN_{(i,j)} \in PND$	power providing node at road arc $(i, j) \in PDTA$

Decision Variables [units]

$TTrsp_{(i,j)}$	1 if road arc $(i, j) \in PDTA$ available, 0 otherwise [binary]

Formulation

$$\min_{PY, PGen, PLdS, Y, Z, Dropped, Excess} \sum_{i \in PNG} PGenCost_i \cdot PGen_i + \sum_{i \in PND} PLdSCost_i \cdot PLdS_i + \sum_{(i,j) \in A} Z_{ij} + \sum_{(s,t) \in D, s \neq t} \frac{q}{2} \cdot Dropped_{st} \tag{5.16}$$

$$
\begin{aligned}
&\text{s.t.}(4.7) - (4.14), (5.2) - (5.11) && && \\
&\quad PThresh_{(i,j)} \cdot TTrsp_{(i,j)} \leq Y_{(i,j)} && \forall (i,j) \in PDTA && (5.17) \\
&\quad 0 \leq Y_{(i,j)} \leq u_{(i,j)} \cdot TTrsp_{(i,j)} && \forall (i,j) \in PDTA && (5.18) \\
&\quad TTrsp_{(i,j)} \in \{0,1\} && \forall (i,j) \in PDTA && (5.19)
\end{aligned}
$$

Discussion

The electricity-transport combo-model formulation is also based on our generic formulation (Section 4.1.3). It combines elements from standalone transportation and electric power networks, which we do not repeat here for the purposes of space.

We add a subset of road arcs that connect to intersection dependent on electric power. The required amount of electricity is $PThresh_{(i,j)}$, where the serving power demand node $PPN_{(i,j)}$ provides the electric power.

The objective function is an unweighted, linear combination of the transportation network and electric power network objectives. The combined objective is to minimize the generation cost and the load shed penalty of the electric power, the vehicle hours on each arc and the dropped demand in the transportation model.

Constraint (5.17) sets the decision variable $TTrsp_{(i,j)}$ as a switch determining if $PThresh_{(i,j)}$ is met by the $PPN_{(i,j)}$. Constraint (5.18) activates the transportation arc (i,j) when $TTrsp_{(i,j)} = 1$ and electricity is available. When electricity is not available at intersection i, all connected road arcs are assumed failed due to an accident and switched off. Constraint (5.19) defines $TTrsp_{(i,j)}$ to be binary. The resulting model leads to rerouting of vehicles based on electric power availability at intersections.

Both energy-transportation combo-models models support interdependent infrastructure analysis. We demonstrate their use with simple and realistic networks.

5.2 Interdependent Energy and Transportation Network Analysis

We analyze the function and vulnerability of interdependent energy and transportation networks using the combo-model approach. We use fuel and electricity networks developed in Ch. 4 and connect them to transportation networks developed by Routley (2020). We complete the following analyses:

1. A simple transportation network from Routley (2020) dependent on the simple fuel network from Ch. 4;
2. the simple transportation network from Routley (2020) dependent on the simple electric power network from Ch. 4;
3. A realistic transportation network developed for the island of St. Thomas from Routley (2020) dependent on the realistic fuel network from Ch. 4; and,
4. A realistic transportation network developed for the island of St. Thomas from Routley (2020) dependent on the realistic electric power network from Ch. 4.

5.2.1 Simple Energy and Transportation Networks

We adapt the simple transportation network from Routley (2020, p. 29) for interdependent analysis. It consists of 13 nodes connected by roadway arcs:

- **3 population nodes:** Population nodes act as origins for trips to and from locations of supply (e.g., a grocery store). Each population node represents an entire community with a population of 2,000. Drivers at each population node demand fuel, grocery, or hardware commodities, dictating destinations. The number of cars and commodity requirements are calculated using values from Routley (2020) for St. John.
- **1 grocery node:** The grocery store acts as a destination and is connected by a separate arc to the 4-way crossing, marked with a dotted circle.
- **1 hardware node:** The hardware store acts as a destination and is connected by a separate arc to the 4-way crossing, marked with a dotted circle.
- **1 fuel node:** The gas station acts as a destination is connected by a separate arc to the 4-way crossing, marked with a dotted circle.
- **1 port node:** The port acts as an origin for trips to resupply grocery stores, hardware stores, and gas stations. The port is in the south-west and is connected by a street (arc)

to the 4-way crossing, marked with a dotted circle.

- **6 transshipment nodes:** These nodes connect roads together and act as intersections. The do not act as origins or destinations.

Figure 5.1 shows the simple transportation network with the effects of a roadway disruption. The connection between the population node population001 and the 4-way intersection is assumed to be unavailable (e.g., due to flooding) and cannot be used. This effect only impacts driver routing as vehicles leaving from and returning to population001 must drive through the center of the island to access food, gasoline, and hardware. We use this disrupted system for all interdependent analyses with simple networks.

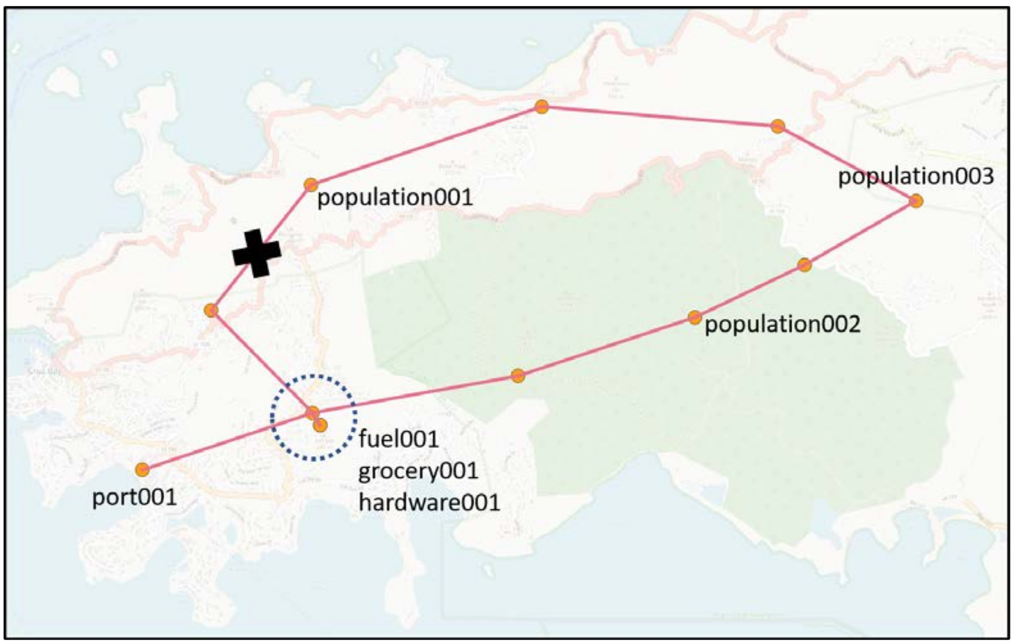

Figure 5.1. Simple Transportation Network with a Disrupted Road. Routley (2020) created a simple transportation model to demonstrate traffic and rerouting of vehicles with the roadway and supply chain transportation model. The simple network is designed to simulate a portion of the island of St. John. It has one grocery store, one hardware store, and one gas station connected to a 4-way intersection (marked with a dotted circle). There are three population nodes and one port node that require access to these locations to access critical supplies and restock supplies, respectively. A failure of a road between population001 and the 4-way intersection leads to rerouting of cars through the center of the island. Figure adapted from Routley (2020, p. 29).

Simple Fuel and Transportation Networks (Gas Stations)
We assess the dependency of gas stations in the simple transportation network (Figure 5.1) on the delivery of fuel via the simple fuel network (Figure 4.2). Here, we assume that the gas station node (fuel001) is supplied by a the simple fuel network at node FN3. If the fuel threshold at the supplying node FN3 is not met, then drivers that need gasoline will not travel. The flow in this network is modeled as an arc-node dependency and solved using the fuel-transportation combo-model formulation.

Figure 5.2 displays routes drivers take with and without fuel network disruptions and the maximum travel times for drivers to acquire commodities are presented in Table 5.1. When there is no fuel network disruption, roads are near capacity due to drivers routing through the center of the network. Instead, when fuel arc (FN2, FN3) is disrupted and prevents fuel reaching FN3 (see Figure 4.4), the gas station is assumed to be unavailable and all drivers from the population centers do not travel.

Table 5.1. Maximum Travel Times in Simple Fuel and Transportation Networks [min].

Scenario	**Grocery**	**Fuel**	**Hardware**
No Failure	49.00	49.00	49.00
Fuel Arc Broken	29.32	N/A	29.32

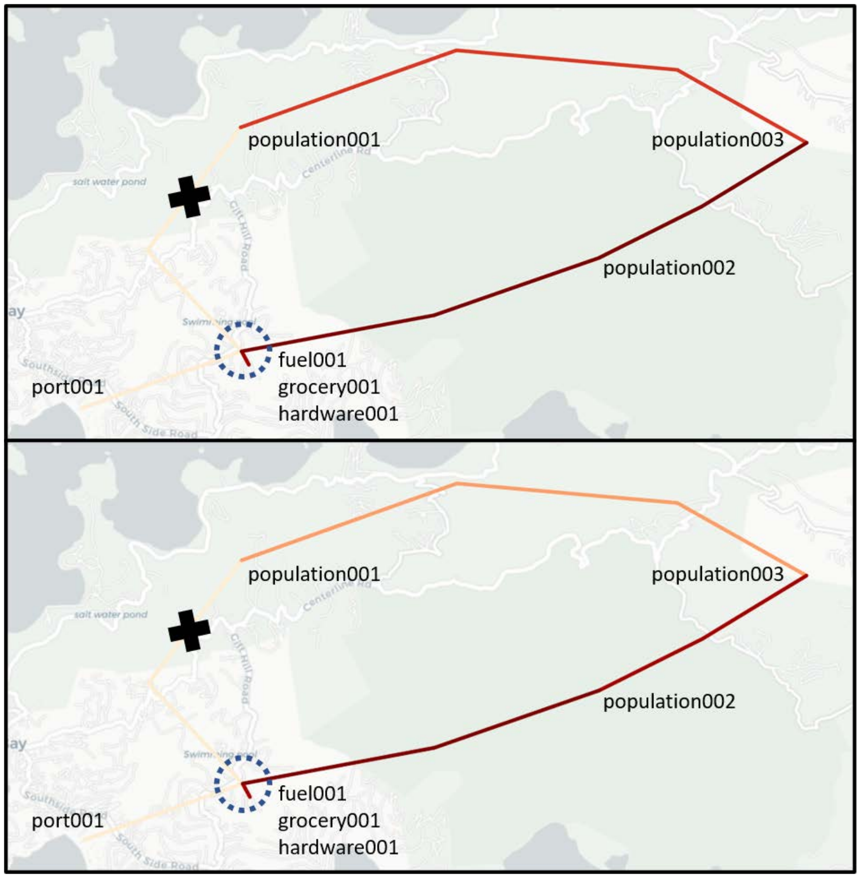

Figure 5.2. Comparison of Traffic Density on Simple Transportation Network with Broken Fuel Arc. The top figure shows the traffic density (darker is higher) without any disruptions to the simple fuel network (see Figure 4.2). The bottom figure shows the traffic density with a disruption to the simple fuel network impacting the gas station fuel001 (see Figure 4.4). Due to the small size of the network, all driving routes remain the same. However, traffic density drops after a fuel pipeline disruption as drivers wanting to buy gas stay at home and become dropped demand.

Tables 5.2 and 5.3 present model objective values and dropped demands in the simple fuel and transportation networks. While the effects of this fuel disruption leads to fewer cars on the road and shorter travel times for drivers traveling to the grocery and hardware stores, the negative effects of fuel network failures are captured via model objective values and dropped demand. Here, we see that the failure in the fuel network causes a significant increase in both fuel and transportation network objective values. The total combined objective becomes 11 times larger given a single arc disruption. This is due to significant dropped demand in both networks. Whereas no demand is dropped before the pipeline failure, both 100 bbl of fuel is undelivered and 1200 people cannot access needed fuel via the transportation network.

Table 5.2. Objective Values in Simple Fuel and Transportation Networks.

Scenario	Fuel	Transport
No Failure	100.02	2,036.29
Fuel Arc Broken	15,000.01	7,847.23

Table 5.3. Dropped Demand in Simple Fuel and Transportation Network.

Scenario	Fuel	Transport
No Failure	0	0
Fuel Arc Broken	100	1,200

Simple Electric Power and Transportation Networks (Traffic Lights)

We assess the dependence of traffic lights in the simple transportation network (circled, Figure 5.1) on the delivery of electricity via the simple electric power network (Figure 4.3). We assume the 4-way intersection in the simple transportation network is dependent on electric power from node d1 in the simple electric power network. We also assume that when traffic lights are not working for this intersection, that traffic can not pass the intersection (e.g., an accident occurs and the intersection becomes blocked). This is modeled as an arc-on-node dependency using the electric-transport combo-model formulation.

We solve for the routes communities take with and without a power line failure. Figure 5.3 shows the power line failure and Figure 5.4 shows the resulting traffic flows. Given a power line failure that prevents electricity from reaching node d1, the 4-way intersection in the simple transportation network becomes unavailable. Blocking this key intersection prevents drivers from reaching any commodities and all traffic becomes dropped demand.

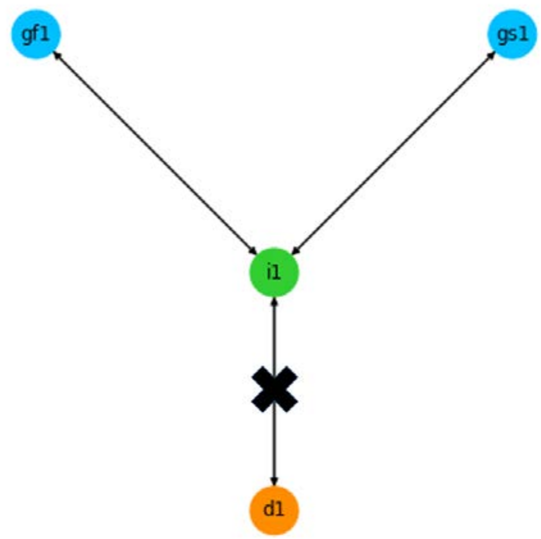

Figure 5.3. Simple electric power network with power arc (i1, d1) failing.

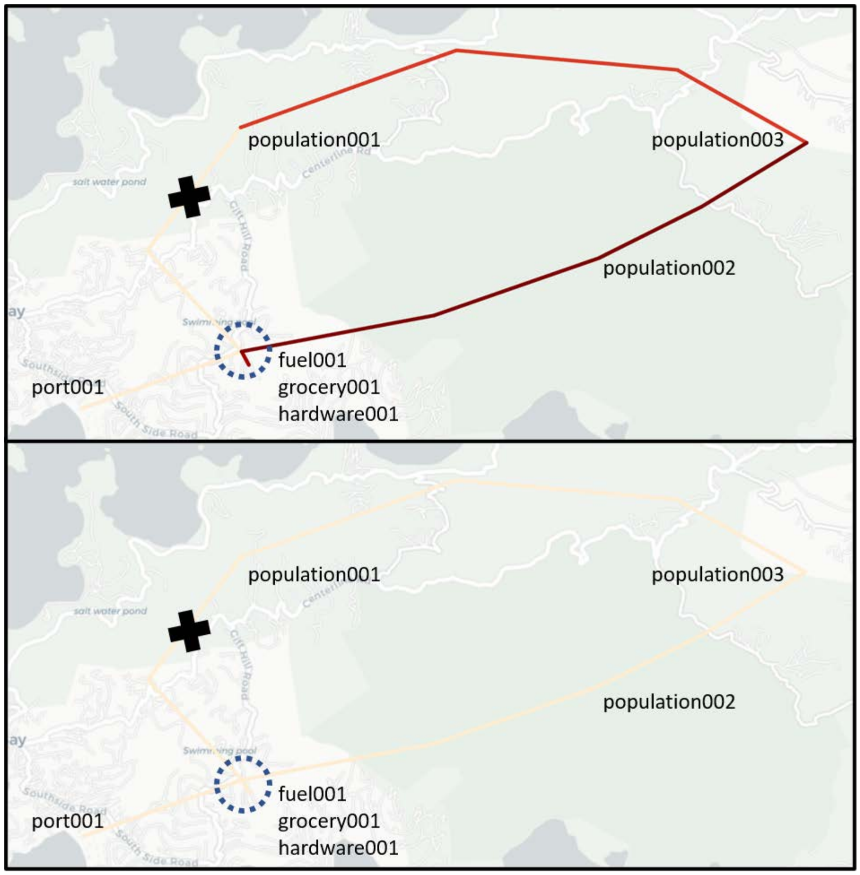

Figure 5.4. Comparison of Traffic Density on Simple Network with Broken Electric Power Arc. The top figure shows the traffic density (darker is higher) without any disruptions in the simple power network. The bottom figure shows the traffic density with the broken power line (i1, d1) (see Figure 5.3). Due to lost of traffic signals at intersections, critical supplies are blocked and all drivers in the simple network become dropped demand.

This is supported by the resulting objective values and dropped demands for the dependent solve. Table 5.2 shows the objective values before and after the power line failure, where the objective value of both models increases by a factor of 7 or more. Table 5.5 shows the dropped demand for both models. There is a demand of 400 units of fuel, 400 units of grocery and 200 units of hardware at each population center. These and the 3 units of demand at the port sum up to 3,003 people unable to access supplies.

Table 5.4. Objective Values in Simple Electric Power and Transportation Networks.

Scenario	**Electric Power**	**Transport**
No Failure	700.00	2,036.29
Power Arc Broken	5,250.00	18,018.00

Table 5.5. Dropped Demand in Simple Electric Power and Transportation Networks.

Scenario	**Electric Power**	**Transport**
No Failure	0	0
Power Arc Broken	70	3,003

Overall, results with these simple networks emphasize the importance of considering fuel and electric power dependencies in transportation networks. The loss of fuel commodities can lead to drivers rerouting to another gas station (if available), or staying home (if not). Similarly, the loss of traffic lights at key intersections can cause large disruptions by forcing drivers to take new routes or making multiple commodities unreachable.

5.2.2 Realistic Energy and Transportation Networks

We demonstrate the energy and transportation combo-models for realistic networks at the scale of a real island or military installation. We study a realistic roadway transportation and supply chain network representing roads, population centers, ports, and supply chain infrastructure on the island of St. Thomas in the USVI.

The St. Thomas network was developed by Routley (2020) for analyzing the effects of flooding on community access to critical supplies (Figure 5.5). The island of St. Thomas has a population of roughly $50,000$, with a hilly geography and numerous winding roads that lead to slow driving and significant traffic. In the network, there are 108 population centers, 1 port, 20 grocery stores, 6 hardware stores, and 14 gas stations. Solving a network flow problem is necessary to determine if the existing road network has sufficient capacity for communities to access supplies and return home within a curfew period. The analysis by Routley (2020) shows the network does have sufficient capacity when all roads are available. However, during worst-case flooding, some communities may be isolated and unable tor reach gas stations, grocery stores, and hardware stores.

Figure 5.5. St. Thomas Transportation Network created by Routley (2020). Roads connected by intersections (yellow) allow population centers and ports (black) to access grocery stores, gas stations, and hardware stores (green, red, and blue). All data necessary to solve the roadway transportation and supply chain model is embedded in this network, including roadway capacities, maximum speeds, and population densities. We refer the reader to Routley (2020) for full network data and explanation.

The St. Thomas network was not originally developed for interdependent infrastructure analysis. We use our combo-model framework to link this model to the realistic energy networks presented in Section 4.2.2. These dependencies are fictional as the realistic energy networks are not the true networks on St. Thomas. Still, they represent realistic dependencies that may affect the St. Thomas system. Thus, this analysis shows the efficacy of the combo-model framework and some realistic effects of failures at gas stations and intersections.

Realistic Fuel and St. Thomas Transportation Networks (Gas Stations)

We assess the fictional dependency of gas stations on St. Thomas on the realistic fuel network from Section 4.2.2. We assume that the 14 gas stations in the St. Thomas transportation network correspond to the 14 demand nodes in the realistic fuel network. Assign each gas station node to a demand node in the fuel network. We also assume fuel network nodes are linked using pipelines that follow roads. The result is the realistic fuel network projected to the island of St. Thomas (Figure 5.6). The full list of fuel-transport dependencies are presented in the Appendix A.1.

Figure 5.6. Realistic Fuel Network from Ruether (2015) Projected on St. Thomas. We relate the realistic fuel network from Ruether (2015) to the realistic transportation network by projecting it on to the island of St. Thomas. Red nodes represent supply and demand nodes. Network connectivity via pipelines are shown in black. Dependencies between networks are listed in Appendix A.1.

We analyze the effects of a worst-case interdiction of two pipelines in the realistic fuel network on the interdependent St. Thomas transportation network (Figure 5.7). Alderson et al. (2015) identify the two worst pipeline arcs to fail are (FN2, FN7) and (FN9, FN13). We implement this failure and solve the St. Thomas fuel-transport combo-model. Resulting flows in the realistic fuel network are shown in 5.7. The worst-case interdiction of two fuel arcs lead to an outage of 5 fuel demand nodes.

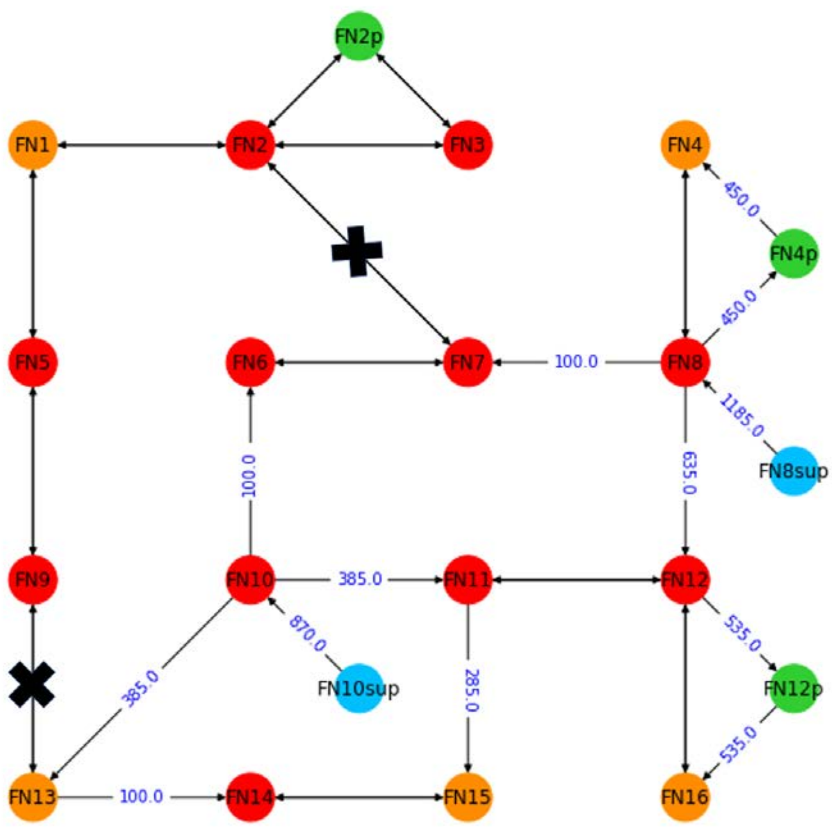

Figure 5.7. Realistic Fuel Model with Worst-Case 2 Broken Arcs. Fuel arcs (FN2, FN7) and (FN9, FN13) are broken and not usable by the model. Model by Alderson et al. (2015, p. 10).

We show transportation network flows before and after fuel pipeline failures in Figure 5.8. Prior to fuel network failures, there are few vehicles traveling through the central portion of island. After two pipelines fail in the fuel network, 5 gas stations on St. Thomas cannot receive fuel (marked with a cross). As fuel is unable to reach these locations, drivers on the eastern coast of the island must now cross the center of the transportation network to acquire fuel at the 9 other gas stations. This results in significantly more congestion in the central and southern portions of the island.

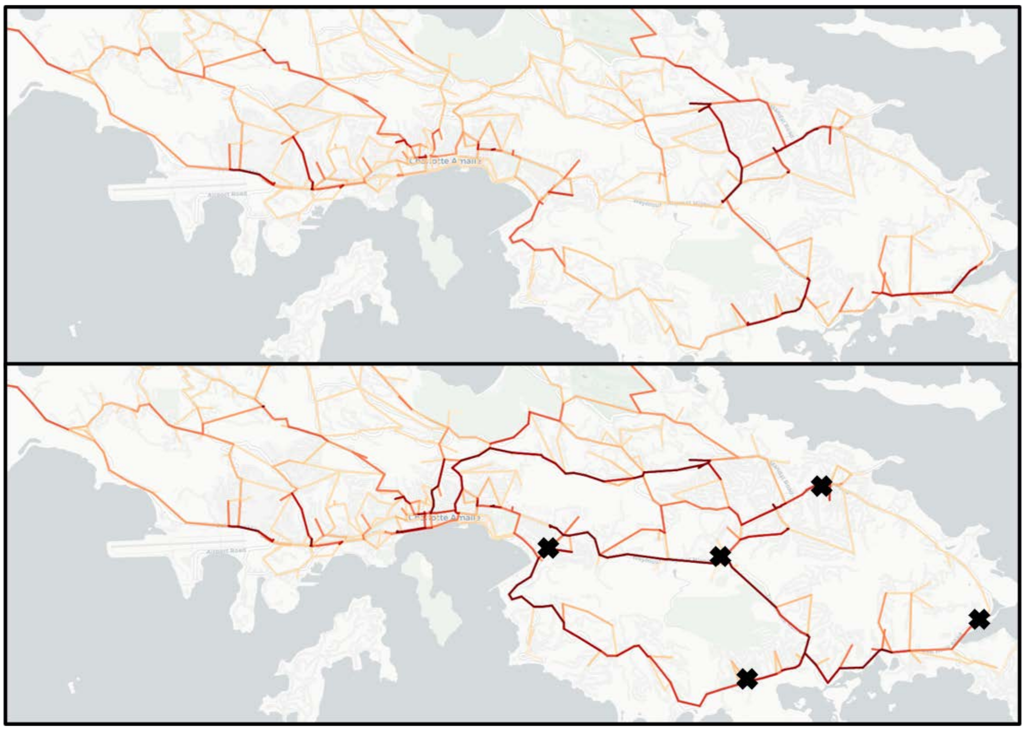

Figure 5.8. Comparison of Traffic Density on St. Thomas with Two Broken Fuel Arcs. The top figure shows the traffic density (darker is higher) without fuel network failures. The bottom figure shows the five gas stations shutdown from fuel network failures and resulting traffic flows.

We measure the impact on communities using the travel times, objective values, and dropped demands for each scenario. Table 5.6 presents the increased maximum travel time for drivers given the fuel network disruption. Before any failures in the fuel network, the maximum round-trip travel time for drivers is between 35-38 minutes. After the fuel disruption, maximum travel times to acquire all supplies increases. The additional congestion on roads makes drivers traveling to a grocery store or hardware store to take slightly longer. Importantly, time to acquire fuel more than doubles from 36 to 79 min.

scenarios and dropped demand This outage of 5 gas stations, which are also the 5 most eastern gas stations on the island leads to a higher traffic on the roads on the eastern part of the island, which can be seen very distinctly in Figure 5.8, where the base case with all gas stations working is displayed on the top part of the figure. On the bottom part is shown, how the traffic density is like, when the population in the east has to travel to the west to get gas. So the outage does not lead to a dropped demand, but it leads to increased traffic on the roads.

Table 5.6. Maximum Travel Times in Realistic Fuel and St. Thomas Transportation Networks.

Scenario	**Grocery**	**Fuel**	**Hardware**
No Failure	35.68	36.30	38.36
Fuel Arc Broken	35.96	79.28	39.81

Tables 5.7 and 5.8 present the objective values and dropped demand for realistic fuel-transport model before and after fuel network failures. The loss of pipelines leads to 512.6 bbl of dropped demand in realistic fuel network, corresponding to an objective value increase of nearly 18 times. Increased congestion and dropped demand in the transportation network corresponds to the objective value increase 1.7 times. Together, these impacts mostly impact fuel access and roadway congestion in the eastern part of St. Thomas.

Table 5.7. Objective Values in Realistic Fuel and St. Thomas Transportation Networks.

Scenario	**Fuel**	**Transport**
No Failure	4,460.26	2,229.50
Fuel Arc Broken	79,850.21	3,796.04

Table 5.8. Dropped Demand in Realistic Fuel and St. Thomas Transportation Networks.

Scenario	**Fuel**	**Transport**
No Failure	0	0
Fuel Arc Broken	512.5	5

Realistic Electric Power and St. Thomas Transportation Networks (Traffic Lights)
We assess the fictional dependency of traffic lights on St. Thomas on the realistic electric power network from Section 4.2.2. We projected bus nodes from the realistic electric power model on to St. Thomas and connect busses by powerlines along roads. Then, we identified 35 intersections on the island of St. Thomas that have large traffic flows and traffic lights. We assume these intersections depend on electricity from nearby electric buses and associated demand nodes. The result is an electric power network projected to the island of St. Thomas, where the transportation network is dependent on (Figure 5.9). The full list of electric-transport dependencies are presented in the Appendix A.1.

We assess the impacts of 3 simultaneous failures in the realistic electric power network on dependent electric-transport systems. We assume bus failures at d101, d102 and d107, which disconnect three demand nodes from the electric power network. The resulting impacts on electric power network operations are shown 5.10. In general, there are few changes in power flows as the loss of demand nodes only reduces generation and flow requirements.

However, the loss of three electric power nodes has significant impacts on traffic in St. Thomas. Resulting interdependent traffic flows are shown in Figure 5.11. The three failed power nodes supply electricity to 19 intersections on a major road in the central portion of St. Thomas. This road traverses the capital city on St. Thomas (Charlotte Amalie) and connects the airport and city from west to east. As a result, we see increased traffic congestion around the deactivated intersections, through the northern portion of the island, and across the south east.

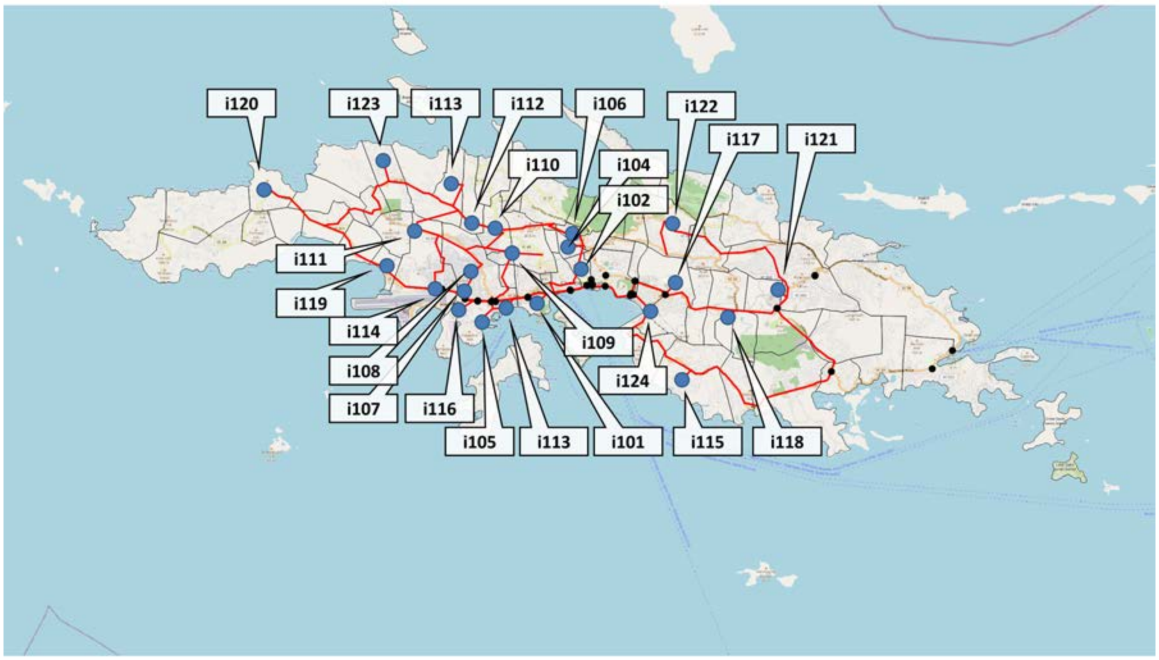

Figure 5.9. Realistic Electric Power Network from Ruether (2015) Projected on St. Thomas. We relate the realistic electric power network from Ruether (2015) to the realistic transportation network by projecting it on to the island of St. Thomas. Blue nodes represent buses within the electric power network. Black nodes represent intersections from the Routley (2020) model that require electricity. Dependencies are listed in Appendix A.1.

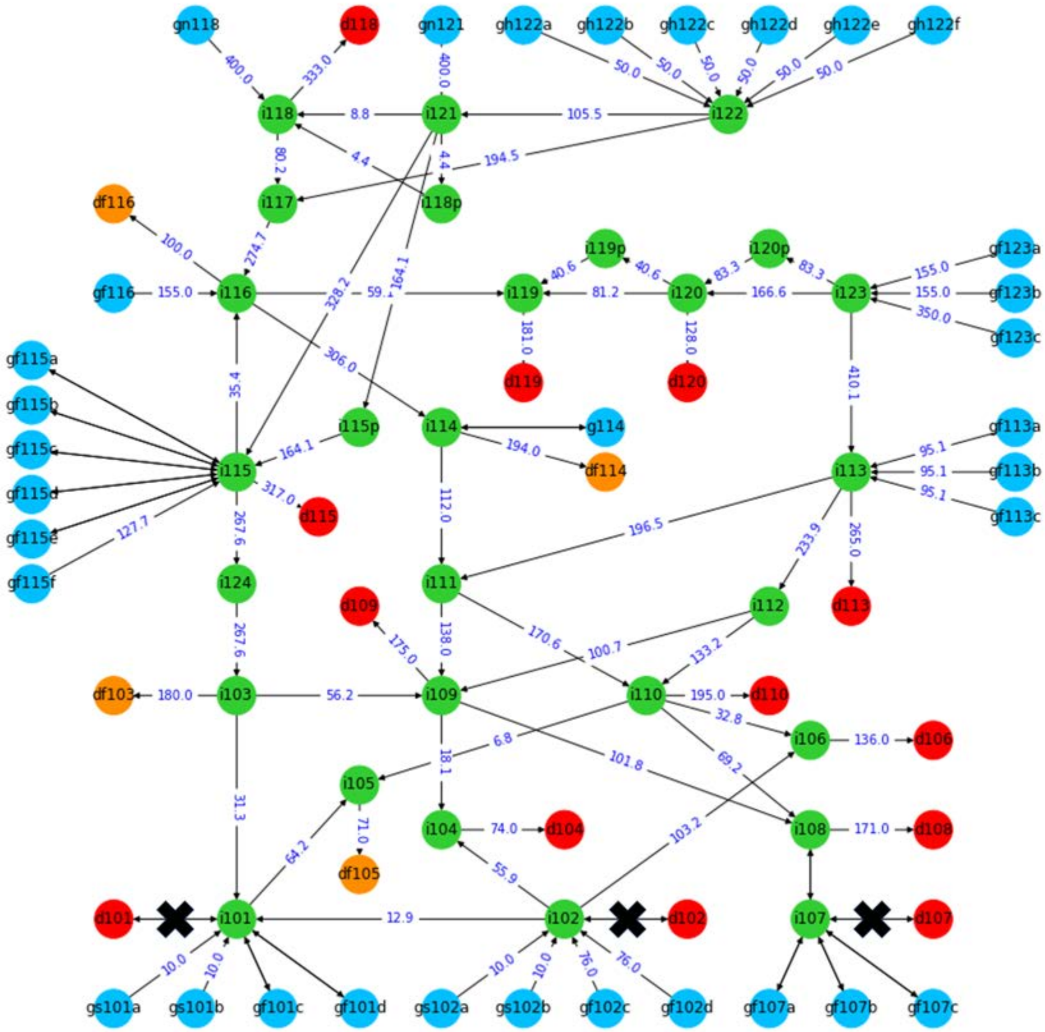

Figure 5.10. Realistic Electric Power Model with 3 Broken Arcs. Power Demand Nodes d101, d102, and d107 are not usable by the model.

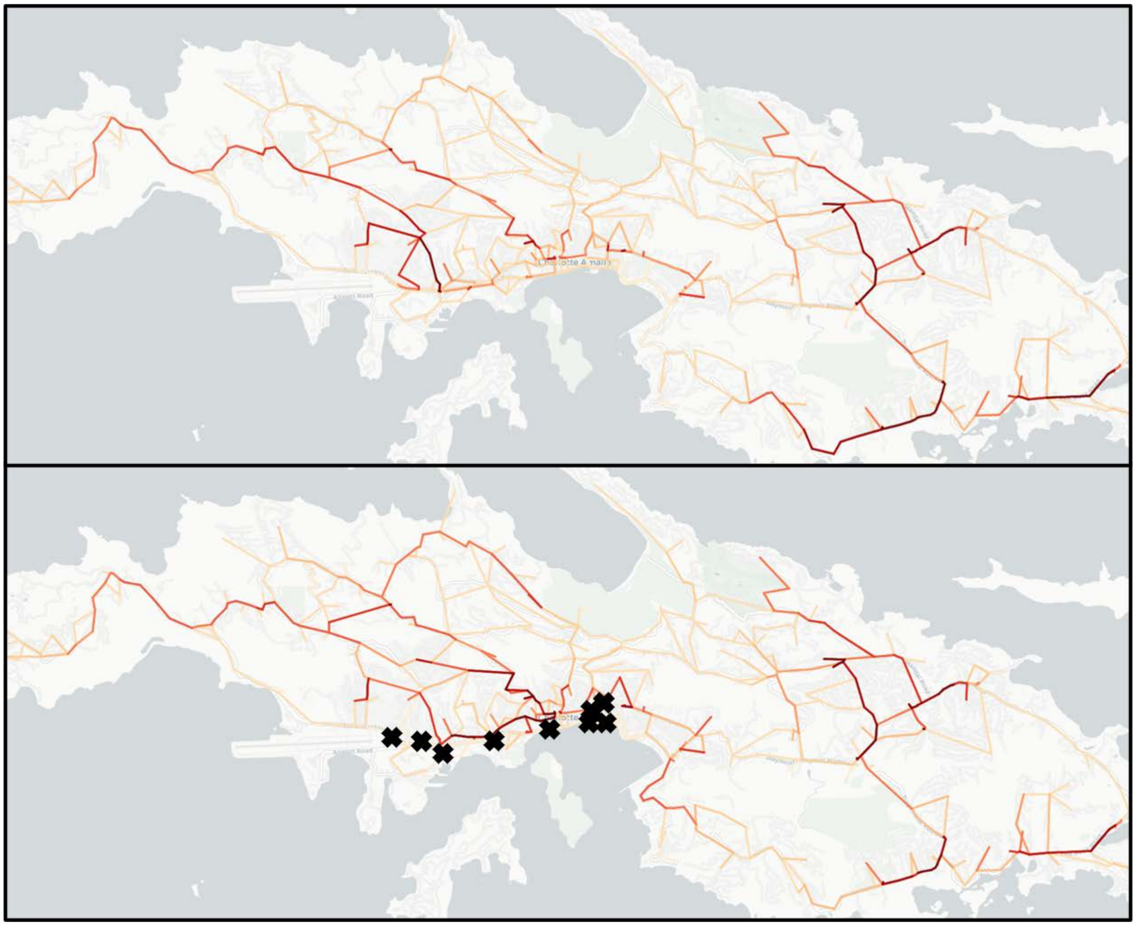

Figure 5.11. Comparison of Traffic Density on St. Thomas with Electric Power Outages. The top part shows the traffic density (darker is higher) without problems and the bottom part shows the traffic density with electric power outages on demand nodes d101, d102 and d107. The position of the affected intersections is marked. Model by Routley (2020).

Table 5.9 shows the maximum travel times with and without the electric power failure. Results show that loss of traffic lights and failed intersections increases the travel time for communities to access grocery stores and hardware stores, but has a small effect on travel time to gas stations. This occurs because four of the grocery stores serving western St. Thomas are located near the airport, where power outages make them unreachable. As a result, western communities must cross the entire island to access food, with moderate increases in travel time for hardware for the same reason.

Table 5.9. Maximum Travel Times in Electric Power and St. Thomas Transportation Networks.

Scenario	Grocery	Fuel	Hardware
No Failure	35.68	36.30	38.36
Fuel Arc Broken	77.46	35.06	46.70

The combined effects on electric power dependent transportation networks are measured in Tables 5.10 and 5.11. Results show moderate increases in the objective values due to limited dropped demand and increased travel times across the island. A greater number of people cannot reach their intended supplies by become stranded due to failed intersections.

Table 5.10. Objective Values in Electric Power and St. Thomas Transportation Networks.

Scenario	Electric Power	Transport
No Failure	84,900.80	2,229.50
Power Arcs Broken	97,817.00	3,041.23

Table 5.11. Dropped Demand in Electric Power and St. Thomas Transportation Networks.

Scenario	Electric Power	Transport
No Failure	0	0
Power Arcs Broken	330	58

5.3 Summary

We demonstrate the extensibility of our combo-model framework by studying interdependent energy and transportation networks. We implement a roadway transportation and supply chain model and study effects of energy network failures on traffic rerouting and access to critical supplies. The transportation model was not designed for interdependency analysis, but we easily generated fuel and electric power dependencies with our combo-model methods. We study fictitious networks to show the effects of fuel and electric power failures on simple and realistic transportation networks.

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CHAPTER 6:
Conclusion

The goal of this thesis was to develop a standard way to consider CIS interdependencies using optimization models. CIS rely on each other to function (e.g., electricity depends on water, and vice versa). Studying a single system in isolation may ignore key dependencies that influence vulnerabilities and cascade failures across systems. This concept of interdependencies is not new, and significant research has been completed that classify, model, and measure the effects of interdependencies on CIS function and vulnerabilities. However, upon review of this literature, we did not find any generic approach capable of connecting pre-existing CIS models for analysis. We built upon this literature, to create and implement a method to link infrastructure operator models together for interdependent analysis. The result is a mathematical and computational framework that easily combines CIS models and supports vulnerability analysis of their interdependent function.

6.1 Generic Combo-Model, Validation, and Use

We use the IMN model developed by Enayaty Ahangar et al. (2020) as a basis for our computational framework. Whereas an IMN model requires full knowledge of interdependencies in model formulation, we deconstructed this approach and built on past studied by Dixon (2011), Alderson et al. (2015) and Ruether (2015) to link unrelated models together. We call these combined models *combo-models*. A combo-model enables interdependency analysis by combining two pre-built Pyomo network flow model objects, modifying their shared objectives, and adding subsets, parameters, decision variables, and constraints. The result is an interdependent network flow model that solves flows over multiple systems and incorporates their physical dependencies. We implement this straightforward approach in a combo-model generator function that works with any Pyomo network flow model via simple user input.

We validate our combo-model generator function by measuring flows over well-studied systems. For this we used the fuel and electric power networks created by Dickenson (2014) and Ruether (2015). Previous implementations included interdependencies in model formulations. Our combo-model methods allows the fuel and electric power networks to be pre-built without dependencies. Then, we add dependencies using our generator function. This approach is flexible to populate models with different data sets. We validate the resulting interdependent energy networks using simple and realistic networks. The simple energy combo-models validated that the effect of interdependencies on energy network vulnerability could be measured with our combo-model. We further validated results by recreating analyses previously complete by Ruether (2015) using a newly generated combo-model, built with the combo model generator function.

We use our combo-model method to develop a new assessment of fictitious energy dependent transportation networks. We implement a roadway transportation and supply chain model from Good (2019) and Routley (2020). This model was pre-built in Pyomo and not created with interdependencies in mind. Using our combo-model generator function, we easily create fuel-transport and electricity-transport combo-models.

We assess the vulnerability of simple and realistic transportation networks to dependent energy system failures. The results for simple energy-transportation combo-models validate our methods work and show the possible effects of fuel and electric power network failures on traffic and access to supplies. We further implement a realistic transportation network of the island of St. Thomas developed by Routley (2020) and create dependencies with our realistic fuel and electric power networks by projecting them onto the island. Although models are fictitious, vulnerability analysis with the St. Thomas network show the importance of using dependent or better interdependent network flow models for assessing transportation network vulnerability. Worst-case failures in in the fuel network also lead to significant rerouting of vehicles across the island of St. Thomas to access gas stations. Similarly, relatively small failures in the electric power network leads to significantly longer travel times to access food and hardware.

It is important to emphasize that the transportation model by Good (2019) and Routley (2020) was not developed for interdependent infrastructure analysis. The combo-model method is both simple and straightforward to easily connect CIS models together, even if they currently do not consider dependencies or interdependencies. Moreover, previous analyses only looked at the impact of blocked or flooded roads on traffic rerouting. However, our combo-model method enables easy connection to our realistic energy networks to consider how fuel and electric power system failures also influence traffic.

6.2 Limitations and Future Work

The results of this work suggest many promising possibilities for further research on interdependent CIS. The combo-model methods and generator function simplify the process of combining two unknown models together. One important avenue of research is combining more than two networks and solving these complicated problems to determine their interdependent function and vulnerabilities. For example, using models of this work, it would be possible to create a 3-network combo-model with fuel, electric power, and transportation dependencies united into a single analysis. This integrated assessment could include the effects of blocked roads on the function of fuel and electric power networks. Moreover, additional dependencies can be further considered, such as pipeline and powerline failures causing blocked roads. The more complicated these combinations get, the more nuanced the results when running a vulnerability analysis. This further enables comparison of vulnerability assessments and interdependent system assessments. Still, the combo-model methods are not tied to a specific model, such that future network flow models can also be considered.

One limitation of this work is the combo-model generator function only works with network flow optimization models, but some CIS use simulation models to solve for their operations. An avenue for future research is to combine Pyomo optimization models with Python-based simulation models and consider their federated analysis. For example, Water Distribution Network (WDN) often use simulation or heuristic optimization techniques for determining water pressures and pump settings. This is because of the physical behavior of water with different pressure, depending on the usage of the whole network. There are Python implementations of these models, which could populate a Pyomo model object and be related to an optimization model solve. Connecting these systems requires considering of network time response and simulation behavior. Future work can consider using Pyomo model objects as an intermediary between optimization and simulation models to enable this federated analysis and assessment of interdependent vulnerabilities with WDNs.

Another limitation of this work is we only modeled physical interdependencies. Future work should introduce more types of interdependencies, such as geographic, cyber, or logical. This should be possible with small modifications to the current methods to improve the usability with data like geographic coordinates. The user-interface could be modified to make it even more easy and comprehensible to use the generic combo model generator with these additional dependencies.

Overall, this work is limited, but shows that the combo-model methods and functions can enable many future analyses. This supports the protection and resilience of existing CIS to attacks or natural disaster and supports future planning of robust systems of CIS on islands and military installations.

APPENDIX: Data for Interdependencies

A.1 Dependencies between Simple Networks

A.1.1 Dependencies: Electric Power Network on Fuel

Table A.1. Dependencies of Electric Power Network on Fuel (Simple Model). Node-node dependency.

Dependent Node	**Threshold**	**Providing Node**
gf1	80	FN3

A.1.2 Dependencies: Fuel Network on Electric Power

Table A.2. Dependencies of Fuel Network on Electric Power (Simple Model). Arc-node dependency.

Dependent Arc	**Threshold**	**Providing Node**
(FN2, FN3)	60	d1

A.1.3 Dependencies: Transportation Network on Fuel (Gas Stations)

Table A.3. Dependencies of Transportation Network on Fuel (Gas Stations) (Simple Model). Arc-node dependency.

Dependent Arc	**Threshold**	**Providing Node**
(tsn002, fuel001)	80	FN3

A.1.4 Dependencies: Transportation Network on Electric Power (Intersections)

Table A.4. Dependencies of Transportation Network on Electric Power (Intersections) (Simple Model). Arc-node dependency.

Dependent Arc	**Threshold**	**Providing Node**
(tsn002, fuel001)	60	d1
(tsn002, grocery001)	60	d1
(tsn002, hardware001)	60	d1
(tsn002, port001)	60	d1
(tsn002, tsn001)	60	d1
(tsn002, tsn003)	60	d1

A.2 Dependencies between Realistic Networks

A.2.1 Dependencies: Electric Power Network on Fuel

Table A.5. Dependencies of Electric Power Network on Fuel (Realistic Model). Node-node dependency.

Dependent Node	Threshold	Providing Node
gf101c	285	FN15
gf101d	285	FN15
gf102c	285	FN13
gf102d	285	FN13
gf107a	450	FN4
gf107b	450	FN4
gf107c	450	FN4
gf113a	535	FN16
gf113b	535	FN16
gf113c	535	FN16
gf115a	112.5	FN1
gf115b	112.5	FN1
gf115c	112.5	FN1
gf115d	112.5	FN1
gf115e	112.5	FN1

A.2.2 Dependencies: Fuel Network on Electric Power

Table A.6. Dependencies of Fuel Network on Electric Power (Realistic Model). Arc-node dependency.

Dependent Arc	**Threshold**	**Providing Node**
(FN10, FN6)	180	df103
(FN10, FN11)	180	df103
(FN10, FN13)	71	df105
(FN10sup, FN10)	71	df105
(FN8sup, FN8)	194	df114
(FN8, FN4p)	194	df114
(FN8, FN4)	100	df116
(FN8, FN7)	100	df116
(FN8, FN12)	100	df116

A.2.3 Dependencies: Transportation Network on Fuel (Gas Stations)

Table A.7. Dependencies of Transportation Network on Fuel (Gas Stations) (Realistic Model). Arc-node dependency.

Dependent Arc	Threshold	Providing Node
(tsn116, fuel001)	500	FN16
(tsn125, fuel002)	300	FN4
(tsn194, fuel003)	100	FN12
(tsn195, fuel003)	100	FN12
(tsn206, fuel004)	100	FN11
(tsn226, fuel005)	250	FN15
(tsn234, fuel006)	100	FN14
(tsn377, fuel007)	250	FN13
(tsn433, fuel008)	100	FN7
(tsn437, fuel009)	100	FN2
(tsn438, fuel010)	100	FN6
(tsn551, fuel011)	100	FN3
(tsn572, fuel012)	100	FN1
(tsn622, fuel013)	100	FN9
(tsn672, fuel014)	100	FN5

A.2.4 Dependencies: Transportation Network on Electric Power (Intersections)

Table A.8. Dependencies of Transportation Network on Electric Power (Intersections) (Realistic Model). Arc-node dependency.

Dependent Arc	Threshold	Providing Node
(tsn098, tsn109)	100	df114
(tsn098, tsn099)	100	df114
(tsn098, tsn092)	100	df114

(tsn122, tsn125)	100	d107
(tsn122, tsn133)	100	d107
(tsn122, tsn118)	100	d107
(tsn125, tsn131)	100	d107
(tsn125, tsn119)	100	d107
(tsn125, tsn122)	100	d107
(tsn125, fuel002)	100	d107
(tsn125, grocery001)	100	d107
(tsn143, tsn144)	100	d107
(tsn143, tsn159)	100	d107
(tsn143, tsn133)	100	d107
(tsn143, tsn141)	100	d107
(tsn144, tsn154)	100	d107
(tsn144, tsn143)	100	d107
(tsn144, tsn131)	100	d107
(tsn144, tsn142)	100	d107
(tsn159, tsn160)	100	d107
(tsn159, tsn166)	100	d107
(tsn159, tsn169)	100	d107
(tsn159, tsn143)	100	d107
(tsn159, grocery003)	100	d107
(tsn160, tsn161)	100	d107
(tsn160, tsn171)	100	d107
(tsn160, tsn154)	100	d107
(tsn160, tsn159)	100	d107
(tsn169, tsn182)	100	d107
(tsn169, tsn159)	100	d107
(tsn169, grocery004)	100	d107
(tsn171, tsn181)	100	d107
(tsn171, tsn160)	100	d107
(tsn205, tsn206)	100	d101

(tsn205, tsn215)	100	d101
(tsn205, tsn202)	100	d101
(tsn205, tsn195)	100	d101
(tsn206, tsn210)	100	d101
(tsn206, tsn205)	100	d101
(tsn206, fuel004)	100	d101
(tsn206, population044)	100	d101
(tsn206, tsn193)	100	d101
(tsn262, tsn263)	90	d102
(tsn262, tsn281)	90	d102
(tsn262, tsn258)	90	d102
(tsn262, tsn236)	90	d102
(tsn263, tsn277)	90	d102
(tsn263, tsn262)	90	d102
(tsn263, tsn237)	90	d102
(tsn304, tsn319)	90	d102
(tsn304, tsn293)	90	d102
(tsn305, tsn318)	90	d102
(tsn305, tsn294)	90	d102
(tsn318, tsn325)	90	d102
(tsn318, tsn305)	90	d102
(tsn319, tsn321)	90	d102
(tsn319, tsn325)	90	d102
(tsn319, tsn304)	90	d102
(tsn313, tsn317)	90	d102
(tsn313, tsn311)	90	d102
(tsn337, tsn352)	90	d102
(tsn337, tsn340)	90	d102
(tsn337, tsn333)	90	d102
(tsn343, tsn347)	90	d102
(tsn343, tsn351)	90	d102

(tsn343, tsn341)	90	d102
(tsn389, tsn392)	100	d120
(tsn389, tsn380)	100	d120
(tsn392, tsn399)	100	d120
(tsn392, tsn403)	100	d120
(tsn392, tsn389)	100	d120
(tsn392, tsn381)	100	d120
(tsn399, tsn405)	100	d120
(tsn399, tsn392)	100	d120
(tsn423, tsn433)	100	d120
(tsn423, tsn413)	100	d120
(tsn423, grocery008)	100	d120
(tsn423, tsn414)	100	d120
(tsn402, tsn403)	100	df116
(tsn402, tsn386)	100	df116
(tsn403, tsn407)	100	df116
(tsn403, tsn392)	100	df116
(tsn403, tsn402)	100	df116
(tsn457, tsn466)	100	df116
(tsn457, tsn448)	100	df116
(tsn457, tsn447)	100	df116
(tsn457, hardware003)	100	df116
(tsn553, tsn556)	100	d119
(tsn553, tsn558)	100	d119
(tsn553, grocery013)	100	d119
(tsn553, tsn551)	100	d119
(tsn593, tsn596)	100	d119
(tsn593, tsn589)	100	d119
(tsn596, tsn600)	100	d119
(tsn596, tsn593)	100	d119
(tsn613, tsn623)	100	d115

(tsn613, tsn621)	100	d115
(tsn613, tsn612)	100	d115
(tsn661, tsn667)	100	d115
(tsn661, tsn663)	100	d115
(tsn661, tsn656)	100	d115
(tsn672, tsn674)	100	d115
(tsn672, fuel014)	100	d115
(tsn672, grocery020)	100	d115
(tsn672, tsn670)	100	d115
(tsn173, tsn174)	100	d110
(tsn173, tsn168)	100	d110
(tsn173, population035)	100	d110
(tsn174, tsn199)	100	d110
(tsn174, tsn179)	100	d110
(tsn174, tsn173)	100	d110
(tsn174, tsn157)	100	d110

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