A Proposal for Infrastructure Adaptation and Cascading Failures for Black Swans

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ABSTRACT

Infrastructure managers are continually challenged to reorient their organizations to mitigate disturbances. Disturbances to infrastructure constantly intensify, and the world and its intricate systems are becoming more connected and complex. This complexity often leads to disturbances and cascading failures. Some of these events unfold in extreme ways previously unimagined (i.e., Black Swan events). Infrastructure managers currently seek pathways through this complexity. To this end, reimagined – multifaceted – definitions of resilience must inform future decisions. Moreover, the hazardous environment of the Anthropocene demands flexibility and dynamic reprioritization of infrastructure and resources during disturbances. In this dissertation, the introduction will briefly explain foundational concepts, frameworks, and models that will inform the rest of this work. Chapter 2 investigates the concept of dynamic criticality: the skill to reprioritize amidst disturbances, repeating this process with each new disturbance. There is a dearth of insight requisite skillsets for infrastructure organizations to attain dynamic criticality. Therefore, this dissertation searches other industries and finds goals, structures, sensemaking, and strategic best practices to propose a contextualized framework for infrastructure. Chapters 3 and 4 seek insight into modeling infrastructure interdependencies and cascading failure to elucidate extreme outcomes such as Black Swans. Chapter 3 explores this concept through a theoretical analysis considering the use of realistic but fictional (i.e., synthetic) models to simulate interdependent behavior and cascading failures. This chapter also discusses potential uses of synthetic networks for infrastructure resilience research and barriers to future success. Chapter 4 tests the preceding theoretical analysis with an empirical study. Chapter 4 builds realistic networks with dependency between power and water models and

simulates cascading failure. The discussion considers the future application of similar modeling efforts and how these techniques can help infrastructure managers scan the horizon for Black Swans. Finally, Chapter 5 concludes the dissertation with a synthesis of the findings from the previous chapters, discusses the boundaries and limitations, and proposes inspirations for future work.

To Dad and Ron (my second Dad): Two great men after God's Heart.
I'll always be standing on your guys' shoulders. I miss you both a lot.

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DISCLAIMER

The views expressed in this dissertation are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the U.S. Government.

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CHAPTER 1

INTRODUCTION

The advent of the Anthropocene has created a global acceleration in development, population growth, technological innovation, economic activity, and urbanization (Steffen et al., 2015). From the mid-twentieth century to today and into the foreseeable future, this acceleration is precipitating many societal and cultural paradigm shifts (Lewis & Maslin, 2015). More than half of the world lives in urban rather than rural environments, and this is expected to rise to sixty percent by 2030; now more than ever, populations are dependent on hard infrastructure to live comfortably (United Nations, 2016). Infrastructure has become a supporting feature for nearly every facet of modern society (Grubler, 1990).

Infrastructure and infrastructure managers face a great challenge today: differential change. Infrastructure has historically been designed for durability and stability. However, the effects of the Anthropocene demand greater flexibility and adaptation; and infrastructure education and practices increasingly fail to demonstrate commensurate adaptability (B. Allenby & Chester, 2018). Thus, the rate of global change unapologetically outpaces the adaptive capacity of traditional infrastructure systems (Chester & Allenby, 2019b). This differential change can be observed in daily life with increasingly intense weather events (A. Helmrich & Chester, 2020; Kim et al., 2022; Markolf, Chester, Helmrich, et al., 2021), the COVID-19 pandemic (Carvalhaes et al., 2020), and cyberwarfare (Chester & Allenby, 2020). These events demonstrate that infrastructures are more than unbiased technological enablers of disassociated activities.

Rather, they have an interdependent and impactful role within wickedly complex earth systems (Carse, 2017; Chester & Allenby, 2019a).

This dissertation explores themes and models of infrastructure complexity, interdependency, and failures. The introduction contains the background context of this research, frames overall research questions, and explains the generalized methodologies, results, and outputs. The more detailed results follow as individual chapters. The dissertation will conclude with a synthesis of the entire research effort and proposals for future research.

1.1 Background Concepts

In this section, several general concepts for infrastructure are discussed. These two concepts provide a foundation and justification for the focus areas of this dissertation. The first topic is the complexity of infrastructure, including wicked complexity and the potential for black swan events to emerge from complexity. The second concept is resilience for infrastructure which includes a brief background of its theoretical evolution and the relevance of these theories to infrastructure adaptations. Next, several concepts specific to this dissertation will be introduced.

1.1.1 Complexity for Infrastructure

Framings of complexity for infrastructure are evolving as the effects of the Anthropocene become apparent. It is now clear that infrastructure systems are tied to the interactions and feedback loops between human, built, and natural systems (B. Allenby & Chester, 2018). Consequently, infrastructure complexity has ballooned beyond comprehension in a behavior called *emergence*, where interactions occur at a rate and depth that human minds cannot perceive (Johnson, 2006). The multi-layer, multi-network levels of interdependency and interconnection across many infrastructures are wickedly complex. Infrastructure managers can no longer frame infrastructure as static and obdurate systems. Optimized designs fail to effectively engage the changing environment (Chester & Allenby, 2019a; Markolf et al., 2022). This understanding of infrastructure complexity is inspired by the Cynefin framework in leadership decision-making (Snowden & Boone, 2007), where there are four levels of complexity: simple, complicated, complex, and chaos. Infrastructure systems, which were once complicated (i.e., able to be fully understood via expertise, research, and investigation), have moved into a complex state, veiling understanding and introducing numerous unknown unknowns. The term "wicked complexity" posits that additional forces – wicked problems, technical and social complexity – make it extraordinarily difficult for engineers to gain even a partial understanding of these relationships, as shown in Figure 1.1 (Chester & Allenby, 2019a). Technical complexities come from the accretion of new technologies on top of old and incomprehensible ways network elements can interact (Arbesman, 2016).

Examination of complexity-competence for various infrastructure design approaches indicates that fail-safe approaches are still predominant. These types of designs do not consider a wide range of possible outcomes. Instead, they design for the worst perceivable outcome and construct robust systems to withstand it. However, this approach is increasingly insufficient (Ahern, 2011; Kim et al., 2019). Instead, infrastructure managers need to cultivate the ability to analyze and determine complexity and uncertainty levels and select contextually appropriate design methods (A. Helmrich & Chester, 2020). This sliding scale suggests not that there are optimal design methods but that all design methods have advantages and disadvantages; engineers must know how to use them appropriately. Helmrich and Chester (2020) emphasize that engineers must focus on comprehending the nature of these complexities to discern how infrastructure design and management should shift to be more adaptable.

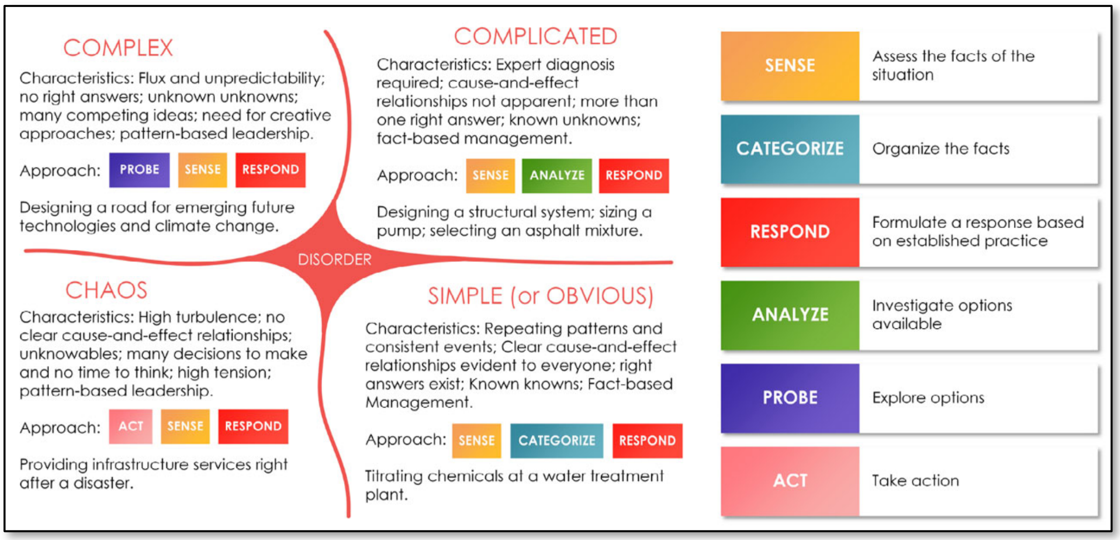

Figure 1.1 – Cynefin Framework for Infrastructure, from Chester and Allenby (2019b). Reprinted With Publisher Permission.

Developed in 1962, Ashby's law of requisite variety claims that stable systems must match or exceed the environment in the number of forms it can take (Naughton, 2017). Originally intended for biology, which has self-organizing systems, Ashby's law relates to infrastructure as a wickedly complex problem. (Boisot and McKelvey 2011) then advanced the requisite variety law and established the law of requisite complexity, which states that "to be efficaciously adaptive, the internal complexity of a system must match the external complexity it confronts." Infrastructure management must meet the environment with requisite complexity to remain viable and effective (Chester & Allenby, 2022).

The concepts in this section state that infrastructure organizations can no longer be simplistic or myopic when designing strategies. The concepts will inform the approach for Chapter 2 when proposing strategies for adaptation in infrastructure organizations. Strategies for infrastructure must be about engaging complexity.

1.1.2 Resilience and Adaptations for Infrastructure

Resilience for infrastructure is multifaceted and should be defined to provide context for the multiple strategies employed to build it. The definition of resilience for infrastructure has evolved from static framings of the simplified "bounce back" to moving forward toward adaptation post-disturbance (Madni & Jackson, 2009; Park et al., 2013; Westrum, 2006). Resilience theory has now moved from static framings to more dynamic framings. Woods (2015) reframed resilience into four concepts:

> (1) resilience as rebound from trauma and return to equilibrium;
> (2) resilience as a synonym for robustness;
> (3) resilience as the opposite of brittleness, i.e., as graceful extensibility when surprise challenges boundaries;
> (4) resilience as network architectures that can sustain the ability to adapt to future surprises as conditions evolve.

Woods (2015) also recognized that systems must balance optimality and flexibility within the system construct. The first three concepts are firmly established and much better understood as part of resilience theory. However, systems and organizations often lack adaptive capacity (Uhl-Bien & Arena, 2018). Additionally, complexity often creates difficulty in identifying actions and attributes which would advance adaptive capacity.

Current research is changing the way infrastructure is perceived. Traditional framings of infrastructure are static and rigid. However, dynamic framings have greater potential to apply Wood's (2015) four-part resilience framework to how infrastructure systems are designed, constructed, and managed. Indeed, resilience for infrastructure is ultimately defined by how the systems adapt and change to their environment. Chester & Allenby (2022) propose four tenants to achieve the requisite variety for infrastructure: 1) sustained adaptation, 2) distributed organizational structures, 3) building capacity for horizon scanning (i.e., systematic search for weak signals that reveal coming disturbances), 4) loose-fit designs that can be repurposed as conditions change.

To implement these four tenants, infrastructure organizations need practical strategies. For example, resilient design principles find that civil infrastructures should be designed in a way that is safe-to-fail (Kim et al., 2019). This concept aligns with Wood's (2015) principle of graceful extensibility, where large pieces of infrastructure may not be capable of morphing but can still fail without degrading the resilience of other systems. Toward resilience in infrastructure organizations, flexible policies and procedures allow for governance restructuring when disturbances occur, decentralizing decision-making and reducing bureaucracy (Chester et al., 2020). Also, there are effective leadership structures for infrastructure organizations that will help balance the tension between administrative and innovative needs and enable new ideas to rise to the surface (A. M. Helmrich & Chester, 2022). Organizations that find balance in the pursuit of organizational efficiency (rigidity – effective during equilibrium) and exploration (innovation – effective during disruption) will be more flexible in the ever-changing environment of the Anthropocene (Markolf et al., 2022). These strategies are practical and reasonable for infrastructure organizations to implement while also moving them toward improved resilience and inform how proposals for resilience will be made in this dissertation.

1.2 Dissertation-Specific Concepts

This section will introduce the three primary concepts for this dissertation. Chapters 2, 3, and 4 cover these concepts more in-depth. However, this section prepares the reader for the primary research objectives in Section 1.3.

1.2.1 Dynamic Criticality for Infrastructure

Given the wicked complexity that infrastructure managers face, strategies for adaptation should focus on building capacity for flexibility during future disturbances (Alderson et al., 2022; Chester et al., 2020). Natural adaptations have been observed in many ecological and anthropological areas. In these adaptations, the systems with the pre-existing adaptive capacity show resilience to environmental changes (Grubler, 1990; Havermans et al., 2015; Pascale, 1999; Roli et al., 2018; Schauppenlehner-Kloyber & Penker, 2015; Tebaldi, 2021). Being wickedly complex infrastructure requires a new level of risk analysis to move toward this adaptive state (Chester & Allenby, 2019a). The environment is changing rapidly, and it is difficult to know what to prioritize; thus, infrastructure organizations should develop useful skill sets in both times of chaos and equilibrium (A. M. Helmrich & Chester, 2022). This contextually appropriate prioritization is called "Dynamic criticality." (Roli et al., 2018). It is a general idea that, to stay relevant, systems must balance robustness with adaptability. However, because – presently – infrastructure systems are not independently flexible, researchers propose that these adaptations must occur organizationally via problem-solving, structural changes, knowledge co-production, and specific leadership strategies (Chester et al., 2020; A. M. Helmrich & Chester, 2022; C. A. Miller & Munoz-Erickson, 2018; Sweet et al., 2014).

Current literature notwithstanding, there is a lack of research on how infrastructure organizations should adapt toward a state of dynamic criticality. Indeed, there are conceptual studies that discuss decision-making concepts for resilience. For example, safe-to-fail concepts will guide designs to choosing sacrificial resources to prioritize higher assets, capabilities, and people (Kim et al., 2019). Infrastructure managers must also be flexible when specifying design relative to the ever-changing environment (Markolf, Chester, Helmrich, et al., 2021). Asset criticality must be determined by how assets enable human capabilities (Clark et al., 2018). However, studies have yet to ask how infrastructure organizations should make decisions for dynamic prioritization. This concept will be explored further in Chapter 2. One of the reasons infrastructure managers struggle to pivot priorities dynamically is a lack of understanding of the complexity of interdependence across different technological infrastructures – which will be discussed in the next section.

1.2.2 Infrastructure Interdependence and Cascading Failure

Infrastructure systems have become interdependent, and simple disturbances may lead to widespread cascading failures (Arbesman, 2016; Rinaldi et al., 2001). The Great Northeastern Blackout demonstrated this phenomenon when a local power line failure in Ohio resulted in a power loss for 445 million people (NERC, 2004). Similarly, a large blackout originated with the failure of one transmission in Arizona, causing widespread power outages across San Diego and failures in other infrastructures, such as water, sewer, traffic, and air transportation networks (FERC & NERC, 2012). Thus, there is a pressing need to understand how interdependencies cause infrastructures to change their interactions and possibly lead to cascading failure. This understanding is necessary so infrastructure managers can build resilience into their systems and manage organizations, customers, and associated stakeholders (Hoff et al., 2023; Hoff & Chester, 2023; Markolf et al., 2018; Ouyang, 2014).

Considering these future risks in the Anthropocene, researchers study infrastructure interdependencies and cascading failure to improve the resilience of organizations and technological systems (Banerjee et al., 2014; J. Li et al., 2019). These fields generally seek to model network interactions and study how disturbances propagate throughout the networks (J. Li et al., 2019). Depending on the need, modeling interdependence and cascading failure are separate methodological challenges, and different research projects may apply one or both. The largest modeling challenge is a lack of access to realistic infrastructure network data (Ouyang, 2014). This restriction prevents models from attaining realistic constructs, which hampers the meaning of research results (Mahabadi et al., 2021). These concepts will be reviewed in-depth in Chapter 3.

1.2.3 Large, Unexpected, and Extreme Disturbances (i.e., Black Swans and Perfect Storms)

A brief discussion of Black Swans is necessary to understand what they are and are not. The term was made popular by Taleb (2007). The concept of Black Swans has specific criteria:

> *First, it is an outlier, as it lies outside the realm of regular expectations, because nothing in the past can convincingly point to its possibility. Second, it carries an extreme 'impact.' Third, in spite of its outlier status, human nature makes us*

> *concoct explanations for its occurrence after the fact, making it explainable and predictable* (Taleb, 2007).

Among the root causes of Black Swans is their tendency to come from highly connected and networked systems. Decentralized systems that are not connected rarely suffer from these large-scale disasters because they do not offer the opportunity for failures to propagate (Taleb, 2014).

Notably, there are often events that may be misconstrued as Black Swans. Often, these are perfect storms, which are the unlikely alignment of multiple relatively well-understood events (Paté-Cornell, 2012). Many historical large infrastructure failures have been called Black Swans but may classify as perfect storms, such as the levy failures and flooding during Hurricane Katrina or the 2003 Northeast Blackout (Leavitt & Kiefer, 2006; NERC, 2004). Care should be taken when applying labels.

However, emergence and the complexity inflicted upon infrastructure systems and their managing organizations bring extreme events' plausibility into question. The complexity that infrastructure is now subject to often pushes the quantity of failure permutations beyond comprehension (Chester & Allenby, 2019a; Johnson, 2006). Thus, events that were once perfect storms may become Black Swans for lack of ability to perceive all the permutations or possibilities. Visualizing these permutations has been the inspiration for interdependence and cascading failure models. It is also the inspiration for an emerging modeling technique.

1.2.4 Synthetic Infrastructure Modeling

The dearth of realistic data for infrastructure networks has inspired some researchers to design models that can generate realistic but fictional networks (i.e., Synthetic). Researchers for power systems have led the way in developing synthetic models. Historically, the power systems community has used benchmark test sets from the Institute of Electrical and Electronics Engineers (IEEE). Test sets have waned in usefulness as electrical engineers seek to answer questions about infrastructure resilience in large-scale networks. IEEE test sets are usually smaller, lacking geographic association (which is desirable), and are often limited to testing only one or a few attributes of power systems (Marcos et al., 2017). As an alternative, the power systems community is developing synthetic models to provide benchmark networks for large areas allowing infrastructure researchers to test new theories and algorithms in a realistic environment (Mohammadi & Saleh, 2021). Similar work is also being done for water systems (Ahmad et al., 2020; Mair et al., 2014; Momeni et al., 2023; Sitzenfrei et al., 2010).

There may be potential for synthetic models to provide research opportunities for the resilience of interdependent infrastructure networks and how they may react to disturbances (Hoff & Chester, 2023). Synthetic models for multiple infrastructures have only recently emerged, so these realistic networks have yet to be used when studying interdependency and cascading failure models (Mahabadi et al., 2021). This combination may yield unique insights for infrastructure resilience principles, particularly as multi-network dependencies change the dynamics and convergence of cascading failures. These potential insights will be explored further in Chapters 3 and 4.

1.3 Problem Statement and Research Objectives

The research objectives for this dissertation arise from concepts in Section 1.2. Indeed, infrastructure management literature lacks clarity regarding how priorities should shift during dynamic scenarios. Indeed, complexity reduces infrastructure managers' ability to sift through overwhelming amounts of data, parse complex systems for root causes, and align their organizations for dynamic prioritization (Chester et al., 2020; Clark et al., 2018; Paté-Cornell, 2012). This dissertation focuses on three areas of research toward infrastructure organizational adaptation: dynamic criticality for infrastructure organizations, modeling possibilities for synthetic and interdependent networks under cascading failure, and testing such models to explore insights for infrastructure resilience. This section discusses the thought process behind the research questions that will guide the remaining Chapters and ends with three primary research questions.

Infrastructure managers need to prepare their organizations to react with speed and variety toward disturbances (Alderson et al., 2022; Boisot & McKelvey, 2011; Chester & Allenby, 2022). The concept of dynamic criticality proposes that infrastructure organizations should balance the skills required to be efficient and those required to be resilient, unlocking skillsets for dynamic decision-making along the way (Markolf et al., 2022; Papachroni et al., 2016a; Turner et al., 2013; Tushman & O'Reilly, 1996). There may be specific activities and organizational attributes that infrastructure organizations should pursue to refine this balance. There appears to be a gap in the literature for these disciplines. While there is some guidance for determining dynamic infrastructure prioritization (Applied Technology Council, 2016a; Clark et al., 2018), there is little knowledge of what skillsets infrastructure organizations should cultivate to facilitate this process. Lacking knowledge of these skillsets, other industrial sectors besides infrastructure may have wisdom and practices to inform how infrastructure should approach dynamic prioritization. Thus, Chapter 2 will conduct an exercise in searching for skillsets from other industrial sectors and contextualizing them for infrastructure.

Additionally, the body of research for infrastructure managers has yet to develop detailed models to visualize realistic dynamics of cascading failure and interdependency (Mahabadi et al., 2021; Marcos et al., 2017). Recently, synthetic infrastructure models have been developed to provide realistic test datasets for new algorithms. There may be additional uses for synthetic networks in conjunction with interdependency and cascading failure models (Y. Wang et al., 2022). However, the theory or research possibilities for such combinations have yet to be explored. Thus Chapter 3 will explore emblematic literature at the intersection of these three types of infrastructure models and discuss potential insights that can be gained from their combination, propose a framework for future development, and discuss barriers to success.

Leveraging the preceding exploration and framework for Synthetic Interdependent Cascading Failure Mods (SICFMs), Chapter 4 will seek to test this concept. Using methodologies from existing research, Chapter 4 will generate two synthetic networks for the same geographical area, fuse them via interdependencies, and simulate cascading failures. The resulting dynamics will be analyzed and discussedin the context of infrastructure resilience and adaptations for infrastructure organizations. Additionally, interdependence in complex human systems often leads to extreme events like Black Swans and perfect storms (Taleb, 2007). These events are impossible to anticipate and carry paradigm-shifting impacts. The Chapter 4 discussion will explore the concept of using SICFMs as a horizon-scanning exercise for extreme event visualization.

Based on the preceding concepts and research needs identified, the following questions are addressed in the subsequent chapters:

1. How do other industrial sectors perform dynamic prioritization, and how can these practices be contextualized for infrastructure? (Chapter 2)
2. How can infrastructure organizations use modeling techniques with realistic infrastructure networks, interdependencies, and cascading failure to gain insight into future extreme events? (Chapter 3)
3. How might cascading failures progress across interdependent infrastructure networks to reveal resilience vulnerabilities and expose potential extreme events? (Chapter 4)

CHAPTER 2

DYNAMIC CRITICALITY FOR INFRASTRUCTURUE PRIORITIZATION IN COMPLEX ENVIRONMENTS

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Chapter Abstract

As infrastructure confront rapidly changing environments, there is an immediate need to provide the flexibility to pivot resources and how infrastructures are prioritized. Yet infrastructures are often categorized based on static criticality framings. We describe *dynamic criticality* as the flexibility and reprioritization of infrastructure and resources during disturbances. We find that the most important prerequisite for dynamic criticality is organizational adaptive capacity through resilience in goals, structures, sensemaking, and strategies. Dynamic capabilities are increasingly important in the Anthropocene, where accelerating conditions, uncertainty, and growing complexity are challenging infrastructures. We review sectors that deployed dynamic management approaches amidst changing disturbances: leadership and organizational change, defense, medicine, manufacturing, and disaster response. We use an inductive thematic analysis to identify key themes and competencies and analyze capabilities that describe dynamic criticality.

These competencies drive adaptive capacity and open up the flexibility to pivot what is deemed critical, depending on the particulars of the hazard. We map these competencies to infrastructure systems and describe how infrastructure organizations may build adaptive capacity toward flexible priorities.

2.1 Introduction

Infrastructure organizations increasingly struggle to respond to accelerating and increasingly uncertain environments, such as extreme weather events (Helmrich & Chester, 2020; Kim et al., 2022; Markolf, Chester, Helmrich, & Shannon, 2021), changing demands, pandemics (Carvalhaes et al., 2020), and cyber warfare (Chester & Allenby, 2020). These changing environments produce a decoupling between what infrastructures can do and what communities need them to do (B. Allenby & Chester, 2018). The diversity of novel hazard dynamics raises questions about whether static framings of *critical* infrastructures (CI) are appropriate (Carlson & Doyle, 2002; Chester & Allenby, 2019b; Gilrein et al., 2019; Markolf et al., 2022). For example, should infrastructure managers prepare for extreme weather-related events in the same way as a pandemic? Do current framings of criticality provide the flexibility to reprioritize resources across various hazards? Throughout this paper, *infrastructures* refer to engineered systems as physical technologies and their associated organizations and governance unless otherwise stated. Furthermore, the *environment* will refer to the many external forces that affect infrastructures, including the natural environment, politics, cyber warfare, disruptive technologies, economic pressures, etc.

Static approaches have long characterized prioritization and resilience strategies for CI (Humphreys, 2019). Since 9/11, many governmental actions, such as presidential directives, congressional acts, and federal department policies, have attempted to inspire greater awareness for critical infrastructure protection and prioritization (Humphreys, 2019). The seminal definition of critical infrastructure came from the Patriot Act and is still used by the Department of Homeland Security (DHS) (CISA, 2019). Multiple lists of prioritized national CIs have been created and contain a mix of traditional civil infrastructures (i.e., those systems considered "utilities") and some social and ecological systems. There does not appear to be a concerted effort to support rapid transitions of resources to different infrastructures sensitive to the hazard. DHS and CISA use a two-tiered priority system for CI but do not have a dynamic prioritization process for when disturbances change (Moteff, 2015). Static framings continue to be standard practice for infrastructure organizations (CISA, 2019; Clark et al., 2018; Moteff, 2015).

Infrastructure organizations often lack the competencies to dynamically prioritize critical systems with quickly changing environments (A. M. Helmrich & Chester, 2022). As disasters unfold, managers need the competencies to make sense of the impacts and the most vulnerable services. COVID-19 is a valuable case study. Whereas energy, water, and other lifeline systems were largely uncompromised, parks (to house and socially distance the homeless) and digital communications became critical to health and well-being (Andrew M. Isaacs, 2020; . criticality and prioritization for infrastructure may change conditionally (Clark et al., 2018); Montgomery et al., 2021). Infrastructure managers need insight into how their organizations should prepare to morph and bend to chaotic events, identify changing environmental conditions, and rapidly pivot priorities. This is referred to as *dynamic criticality*, where a system can contextually adjust to environmental disturbances, dynamically prioritize resources, and balance robustness and adaptability (Roli et al., 2018).

Many CI sectors have diverse operational requirements, so a framework for dynamic criticality must be broadly applicable and focus on infrastructure organizational management and not specific engineered systems. Toward this end, competencies of other sectors that appear to be able to pivot how they focus as hazards change are reviewed, cross-compared, and applied to engineered infrastructures.

2.2 Methodology

Cross-industry sectors that appear to have dynamic criticality capabilities were reviewed to improve the capabilities to dynamically define critical infrastructures and pivot resources depending on specific hazard contexts. Five sectors were selected and analyzed: 1) Leadership and organizational change; 2) Military and defense; 3) Medical emergency and triage; 4) Manufacturing; and 5) Disaster response. Literature was collected based on keyword searches to identify competencies that enable sectors to have the flexibility to reprioritize critical systems and pivot resources accordingly when faced with disturbances. Keywords included dynamic, criticality, edge of chaos, self-organization, decision-making, and priorities. The search used metadata academic journal search engines (ASCE, Google Scholar, Crossref, WorldCat, etc.) and identified twenty-nine sources across journal publications, book chapters, and government reports.

An inductive approach was used to describe common themes to identify sector competencies that support dynamic criticality. Inductive thematic analysis is a qualitative process whereby papers or texts are analyzed to develop common concepts and themes (Boyatzis, 1998; Corbin & Strauss, 1990; Thomas, 2006). The general process is shown in Figure 2.1. The goal was to evaluate how the sectors prioritize critical systems and resources amidst dynamic environments. The inductive analysis followed three steps: content review, theme generation, and validation (Thomas, 2006). In reviewing the literature, themes about the research objectives were identified, labeled, and defined. The themes were analyzed for similarities, subtopics, and associations towards synthesizing them into a generalized framework for infrastructure (Creswell, 2002; Thomas, 2006). Methodologies, vernacular, and lexicons differ between the sectors, but common themes emerged, resulting in a framework with four overarching themes. Lastly, group-sample analysis was used to validate the results (Thomas, 2006).

Figure 2.1 – Process for Inductive Thematic Analysis

2.3 Sector Review

The five sectors identified were examined for their dynamic capabilities. While *Leadership & Organizational Change* reveals generalizable capabilities across many domains, *Military and Defense*, *Medical Emergency and Triage*, *Manufacturing*, and *Disaster Response* show capabilities specific to their industries.

Leadership & Organizational Change: Leadership and organizational change literature transcends specific industries and describes organizations' cultures, priorities, and structures. Organizations have experienced significant transitions in the past century, such as the shift from production orientation to knowledge-production and the associated technological revolutions (Davenport, 2001; Manville & Ober, 2003; Uhl-Bien et al., 2007a). These transitions are entangled with tensions such as supply chain disruptions by logistics or dwindling resources and changing consumer demands (e.g., increased awareness of corporate social responsibility to the latest technology). The transitions also include the restructuring of workplace dynamics (e.g., dispersion of power to remote work) and competition which pressures the speed of innovation within an organization. These tensions interact unpredictably and destabilize organizations (Sterman, 1989; Uhl-Bien & Arena, 2018). Organizations have responded to this complexity with adaptability, recognizing they will be operating with some degree of chaos and disruption, utilizing responses such as dynamic decision-making (DDM) (Brehmer, 1992; Edwards, 1962; Gonzalez et al., 2005).).) Organizations also developed principles like contextual ambidexterity (March, 1991; Papachroni et al., 2016b; Uhl-Bien & Arena, 2018) and leadership priorities that emphasize innovation (Uhl-Bien et al., 2007a). Complexity Leadership Theory (CLT) describes balancing bureaucratic leadership (during times of stability) with more entrepreneurial leadership that emphasizes innovation in the face of chaos. CLT emphasizes the ability of the organization to pivot between efficiency (stability) and resilience as innovation during instability.

Military and Defense: Defense organizations must effectively operate across stable (peacetime) and chaotic (wartime) contexts and have embraced several techniques for assessing the criticality of resources and threats dynamically. The strategic and competitive nature of the military may inspire more proactive planning and decision-making. These techniques include Dynamic Force Employment (DFE), creating scalable and context-specific capabilities to deploy resources in an increasingly chaotic and diverse landscape (DoD, 2018; Wetzel, 2018). Mission command has also adopted decision-making techniques that encourage collaboration and bottom-up formation of relationships, create a continuous dialogue towards a shared understanding, and provide clear command guidance and empowerment for autonomous decision-making (Deployable Training Division, 2020). The core tool that has emerged for assessing threats and responses and how those change with context is Center of Gravity (COG) analysis (Mcfadden, 2014; Schnaubelt et al., 2014). COG is the entity capable of achieving or enabling an objective or capability and can represent physical assets (weapons systems or financial institutions), people (individuals or groups), or ideologies (Kornatz, 2016; Perez, 2012). Defense organizations have centered COG as a framework for assessing threats (e.g., physical armies, financial networks, or ideologies) in differing contexts and surgically deploying responses. COG analysis involves first identifying crucial capabilities (crucial enablers for a COG to function). Next, it identifies critical requirements, i.e., essential conditions, resources, or means for a critical capability to be fully operational. Lastly, COG describes critical vulnerabilities where neutralization, interdiction, or attack will create decisive or significant effects on the COG. The COG analysis guides the operational response, including lines of operation (actions or events that must unfold in a particular sequence) and lines of effort (the linking together of tasks to determine how they will lead to an objective) (Kornatz, 2016; Schnaubelt et al., 2014).

Medical Emergency & Triage: Originally conceived in the 1700s out of necessity to make rapid decisions for wounded soldiers in wartime, medical systems began formally developing triage frameworks in the 1970s (Dippenaar, 2019). Emergency departments require decision-making tools to prioritize groups and individuals during medical emergencies. For triaging groups of patients, the SALT (sort, assess, life-saving interventions, treatment, and transport) and START (Simple Triage and Rapid Treatment) methods focus on sorting and diagnosing. During sorting, these methods quickly place patients into three categories: 1) unresponsive or life-threatening injuries; 2) can respond purposefully; 3) can walk, despite injuries. Based on this sorting, medical providers can prioritize limited resources to assess and care for patients, including life-saving interventions, further care, and transportation. Notably, if providers determine that the patient is unlikely to survive due to the severity of their injuries, they may move on to other urgent patients. While certainly not devoid of ethical conflicts, these frameworks help medical providers rapidly determine criticality and respond accordingly (Aacharya et al., 2011).

Triage for individuals leaves out the "sorting" step and presumes the emergency department is experiencing a steady flow of patients to prioritize. With individuals, an E.R. physician must first assess how quickly a patient needs attention and then how to administer proper care. For example, the Emergency Severity Index (ESI) assesses the patient's condition with a series of questions: 1) immediate life-saving required; 2) high risk, confused/lethargic/disoriented, severe pain/distress; and 3) the number of resources required. ESI combines these questions with vital measurements (heart rate, respiration rate, and oxygen levels). The output is a priority level from 1 to 5, with level 1 requiring immediate medical attention and level 5 requiring medical attention within 120 minutes (Aacharya et al., 2011).

Worldwide triage frameworks exhibit thematic commonalities in determining criticality, despite practical application differences, often driven by culture (Dippenaar, 2019). In general, medical providers quickly identify patients that require immediate care, administer LSIs for stabilization, and then assess the remaining patients with less urgency. Moreover, the individual patient assessment provides a specific checklist of critical body systems and symptoms, which points the medical team toward the type of care needed (Aacharya et al., 2011). Ultimately, triage frameworks save time, energy, and lives when employed properly (Dippenaar, 2019).

Manufacturing: The globalization of markets has increased demand volatility, forcing manufacturing companies away from mass production toward mass customization. Prioritizing market competition and profitability, companies have shifted to designing unique products for individuals at smaller volumes (Hu, 2013). Simultaneously, new technologies have aided manufacturing adaptations, such as advanced sensor systems reducing equipment-based disturbances so manufacturers can focus more on market analysis and the associated manufacturing pivots (Frankowiak et al., 2005). Reconfigurable manufacturing systems (RMSs) have been a pivotal adaptation that has increased the ability to manage the market volatility toward rapid customization. RMSs are individually reconfigurable machines that can be added, removed, or adjusted to customize products to customer needs. The goal of RMSs is to minimize the response time to unpredicted market shifts while still allowing for traditional machine and system-level optimization (Yelles-Chaouche et al., 2021). During the development of RMSs, a new set of organizational requirements emerged: scalability, convertibility, diagnosability, customization, maximizing tasks given to machines, and balancing maintenance for optimal throughput and reliability (Koren et al., 2018). Manufacturers developed methods to detect market disturbances, designing, selecting, and pivoting to new configurations. Two priorities drive these configurations: resource availability (i.e., tools and machines) and throughput requirements (production volumes) (Mabkhot et al., 2020). In general, the frequent and rapid pivots that RMSs must undergo highlight key capabilities: disturbance detection, coupled with a quick redesign and driven by critical priorities.

Disaster Response: The complexity of disaster response arises from shifting climatic conditions in hazard prediction, coordination of limited resources for response and recovery activities, and varying adaptive capacity and vulnerability of affected populations (O'Sullivan et al., 2013). The stress of chaotic environments underscores the importance of heuristics in decision-making (Sterman, 1989) and thoughtfully crafted and practiced response plans (FEMA, 2021; O'Sullivan et al., 2013). During disaster response, institutions identify critical assets for protection in terms of importance, value, sensitivity, associated resource requirements, and interdependencies (FEMA, 2018; Hempel et al., 2018). Traditionally, deterministic methods have dominated disaster response decision-making based on historical data, experiences, and judgment without considering future uncertainties. Some critical values (e.g., water level or flood return period) can provide indices for decision-making. More recently, hazard prediction models use probability and uncertainty modeling (e.g., the relationship between dam failure probability and fatality). Probabilistic approaches can be combined with a real-time hazard assessment to reduce the uncertainty in the decision during disasters but require more information and an iterative process to improve the models, which can potentially delay the decision (Peng & Zhang, 2013).

2.4 Thematic Analysis Results

Several commonalities emerged across the sectors. The thematic analysis revealed four generalizable themes. First, many sectors showed methods for describing *goals* when dynamically shifting priorities. Second, several sectors exhibited capabilities towards configuring organizational *structures* to implement the goals. Third, a common theme of *sensemaking* appeared across sectors: making sense of an environment to open up decision-making (Weick, 1995). Fourth, organizations developed specific *strategies* for implementing flexibility amidst changing conditions. These four themes and their competencies are shown in Figure 2.2 and are discussed at length in this section. These results and Figure 2.2 will guide the following discussion.

2.4.1 Theme 1: Goals

Establishing *goals* was pivotal for sectors to implement dynamic criticality. Goals guide organizations toward responding to disturbances or chaos, which leads organizations to change structures, sensemaking, and strategies accordingly. Goals appear foundational for strategy development. The six competencies that emerged from the goals fell into two primary categories as shown in Figure 2.2. The first was a *rapid adaptation* to changing environments. Rapid adaptation includes self-organizing adaptability, requisite variety, and quick detection and reaction to disturbances. The first category of goals focused on *enabling quick decision-making*, including prioritization of resources during emergencies, identifying critical requirements for mission accomplishment, and building organizational relationships to facilitate dynamic decision-making.

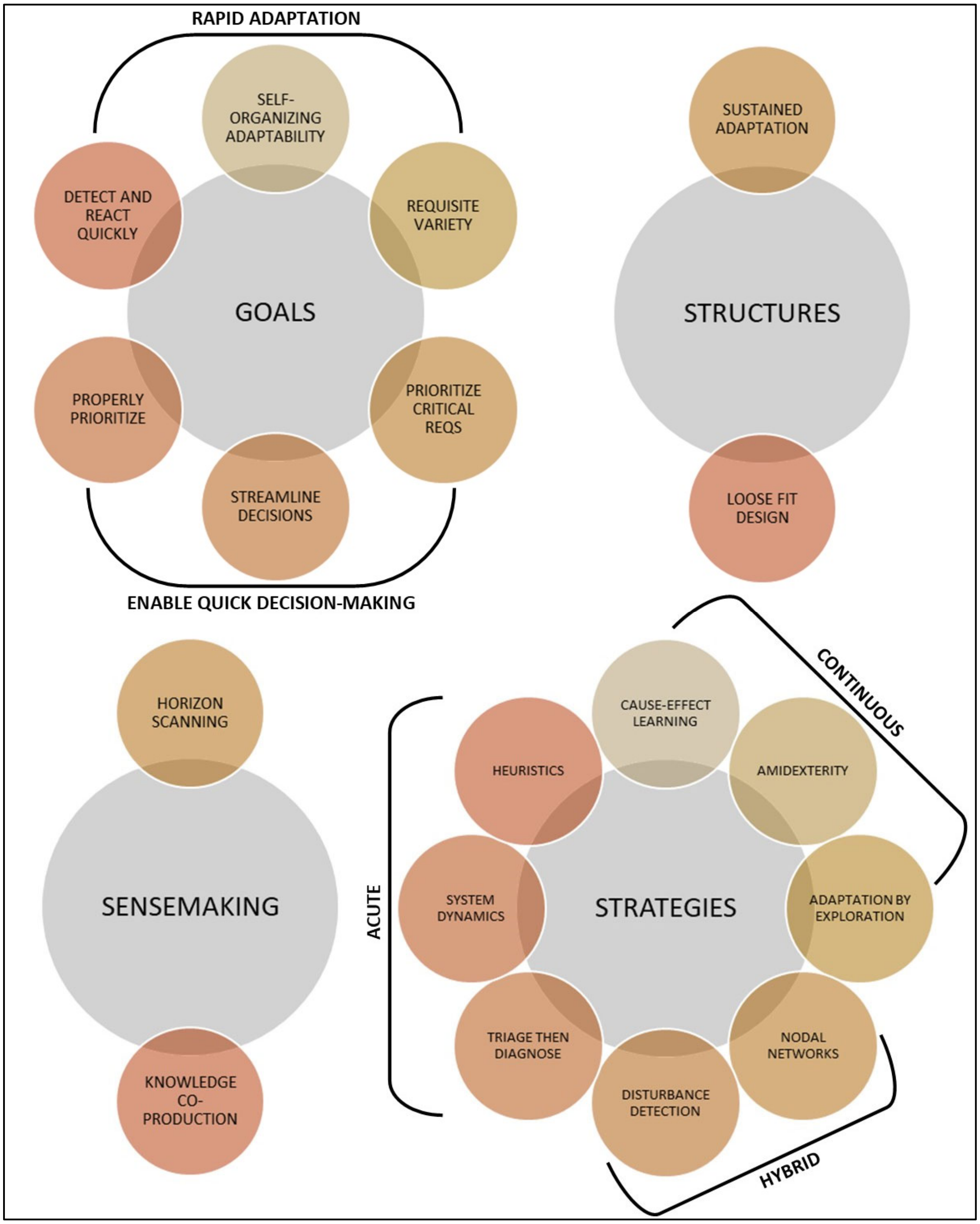

Figure 2.2 – Summary of the Resulting Themes and Competencies.

When organizations set goals for rapid adaptation, this nudges the organization toward dynamic criticality, often indirectly. First, organizations with goals toward dynamic criticality *select priorities* more efficiently than others (Manville & Ober, 2003). Similarly, dynamic environments alternate unpredictably between stability and instability. In response, organizations should develop exploitative efficiency and explorative innovation. Exploitation focuses on efficiency, which is effective during periods of stability, and exploration is more effective during instability. This ambidexterity makes an organization efficient, agile, and flexible (March, 1991; Uhl-Bien & Arena, 2018). Second, *requisite variety* commonly appeared in both military and manufacturing goals. Requisite variety describes how systems in changing environments must have a repertoire of responses sufficient for their environment complexity (Chester & Allenby, 2022; Naughton, 2017). The military changed its operations to incorporate randomness for the timing and movement of forces which simultaneously confuses adversaries and builds adaptability and readiness for deployment (DoD, 2019). In manufacturing, RMSs match market needs and the pace of change (Khalil et al., 2020; Koren et al., 2018). Rapid adaptation goals have also led manufacturing to use sensors, process monitoring, and analysis tools to detect and react to process and equipment disturbances (Frankowiak et al., 2005). For disaster response, the variability of disaster outcomes makes it unrealistic to standardize prioritization methods (such as in medical triage). Thus, disaster planners set general goals toward quick contextual discernment of criticality and speed of response (Applied Technology Council, 2016b; DHS, 2019b). Although the goals found within the thematic analysis were different, they were generally oriented toward rapid adaptation. Ultimately, this appeared to inform organizational priorities, preventing reflexive decision-making.Goals that supported making faster decisions also improved dynamic criticality. The sectors showed many of the same principles for decision-making that (Brehmer (, 1992) cites for the theory of DDM, such as decisiveness, delegation, taking responsibility, and avoiding fixation. In medical triage frameworks, the goal of appropriately prioritizing patients during emergencies is paramount to establishing decision criteria so medical staff can dynamically sort and prioritize patients specific to the scenario without time-consuming analysis, testing, or judgment (Aacharya et al., 2011; Storm-Versloot et al., 2011). Secondly, several sectors set a goal to clarify the requirements needed to meet specific objectives. Military COG analysis uses critical requirements, vulnerabilities, and assets to select priorities for mission accomplishment (Perez, 2012; Schnaubelt et al., 2014). Similar to how military planners need to identify various critical attributes, disaster response planners also must prioritize specific assets and resources during a response (DHS, 2019a; O'Sullivan et al., 2013). As per (Clark et al., 2018), disaster planning seeks to isolate the most critical assets and then shift those priorities dynamically. Also, the military realized that micro-management and lack of trust slowed the decision-making process. So, senior military commanders set goals to streamline the decision-making process. They built organizational relationships that empowered local commanders to prioritize and make decisions swiftly by creating a culture of trust, communication, and deep mutual understanding (Deployable Training Division, 2020).

2.4.2 Theme 2: Structures

The ability of organizations to change their governance models and processes to respond to changing conditions emerged across the sectors. Novel methods for transitioning governing structures appear to enable organizations to see game-changing disruptions and pivot resources more clearly in response. Two competencies emerged, as shown in Figure 2.2: 1) a commitment to sustained adaptation where the organization recognizes that its environment is in flux and structures itself to adjust course as needed, and 2) instituting processes that enable dynamic organizational structures and adaptive planning, referred to as "loose fit design." In CLT, organizations can pivot between efficiency and innovation governance models, the latter suitable for periods of instability (Uhl-Bien & Arena, 2018). RMSs are more flexible at handling demand and disruption shocks, adjusting the systems' orientation in response. RMSs achieve this flexible state through convertibility (capable of adaptation to new products), diagnosability (design quality assurance with the system, and not as an afterthought), customizability (designed around a family of products, and not just one), and scalability (cost-effective adaptation to future market demand). The loose-fit design has several associated properties. First, horizontal governance – shifting resources and decision-making authority to front-line workers who can coordinate and better sense change – creates organizational capabilities to diagnose and respond appropriately to chaos and change quickly. Formally, dynamic planning involves avoiding fixation – remaining focused on a set of increasingly obsolete challenges – and committing to a continuous cycle of reassessment of environmental conditions relative to organizational goals and processes (Brehmer, 1992; FEMA, 2016).

Like how goals inform decisions, organizational structures provide a foundation for sound decision-making. Organizations that confront frequent dynamism have streamlined processes and aligned their formal and informal structures to be more flexible as the environment changes. To maintain readiness, they must suppress natural apathy within structures during periods of equilibrium and maintain energy toward adaptability (Pascale, 2006).

2.4.3 Theme 3: Sensemaking

Dynamic environments forced organizations to develop new ways of understanding and interpreting the environment. In doing so, they are exercising *sensemaking*: taking in new knowledge, structuring it using novel techniques, and ultimately opening up decision-making opportunities (Weick et al., 2005). In the thematic analysis, sensemaking presented two distinct competencies, shown in Figure 2.2: 1) the search for weak signals that may indicate changing environmental conditions in a process called *horizon scanning*; and 2) focusing on organizational *co-production of knowledge*. For DFE, the military collects and interprets data to understand the operational environment, enabling it to alter its force structure dynamically (DoD, 2019). Similarly, disaster response planners for communities spend significant time understanding the dynamic environment within their area of responsibility to anticipate how different disturbances may affect the community (FEMA, 2021; O'Sullivan et al., 2013). Additionally, manufacturing systems constantly scan within their system to detect weak signs of equipment/process failure (Frankowiak et al., 2005) and also scan outside their systems (i.e., markets) to see hints of market changes that may trigger shifts in production or design (Khalil et al., 2020). Organizational co-production of knowledge supports dynamic criticality primarily through network and collaboration. CLT creates informal social networks in organizations, allowing for a freer flow of ideas and collaboration, thus increasing innovation during disorder when old priorities suddenly become irrelevant and new ones must be identified (Uhl-Bien & Arena, 2018).

Similarly, managers of knowledge workers have shifted focus from task oversight towards knowing the capabilities of subordinates and building networked teams, creating more effective organizational knowledge toward shifting priorities during disturbances (Davenport, 2001). Indeed, the military has also identified this need for knowledge co-production with the concept of mission command. Senior commanders have a greater understanding of the strategic environment, while subordinate commanders have a better contextual awareness. Thus, mission command also shifts focus from oversight. The focus on building trust between the higher and lower ranks empowers and supports. The continuous dialogue toward shared understanding establishes trust and liberates senior commanders to focus on giving clear guidance and intent. Subordinate commanders are then empowered to swiftly decide and prioritize without asking for additional guidance (Deployable Training Division, 2020). Collectively, horizon scanning and co-production of knowledge during disturbances seek to combine information collection and synthesis with robust abilities to quickly and efficiently convert that information into relevant priorities.

2.4.4 Theme 4: Strategies

The goals, structures, and sensemaking culminated in the creation of *strategies*. Eight strategies emerged from the review, describing acute (short-term), continuous (long-term), and hybrid decision-making timeframes. Acute strategies address disturbances with an apparent beginning and end (e.g., medical triage). Other sectors used continuous strategies oriented toward cyclical and ongoing problems (e.g., global military competition). Some sectors use hybrid strategies for scenarios with a clear beginning and end but require reassessment (e.g., lifeline disaster response). The three types are grouped and labeled accordingly in Figure 2.2.

The three acute strategies came from the triage and disaster response sectors. Time constraints of medical emergencies and disaster scenarios focus on rapid decision-making using pre-established frameworks, which requires deep systems knowledge to do dynamic criticality. In medical triage, this situational urgency requires *prioritization via predetermined critical information heuristics.* Action and priority-based thresholds are predetermined for efficiency, so a paramedic or triage nurse is not responsible for analyzing the patient's condition. They are trained for condition determination and prioritization via prescribed metrics, charts, data, and sensors (Aacharya et al., 2011), with some flexibility for tacit knowledge and experience to account for framework simplicity (van Pijkeren et al., 2021). Sometimes, medical triage encounters situations where professionals must do *initial sorting & emergency interventions and then detailed evaluation/determinations* – such as in a mass casualty situation. Medical professionals begin with simple visual heuristics for prioritization: unresponsive, responsive, or walking. While simple, it is the most expedient strategy in the results. It displays how organizations can simplify a chaotic environment for tiered criticality prioritization. Emergency managers also found that *in-depth knowledge of the system, connections, capabilities, and dependencies* was an effective strategy to cut through the complexity and chaos during disasters. This knowledge enables decision-makers to make quick but contextualized decisions for prioritization (FEMA, 2021; O'Sullivan et al., 2013). While building and maintaining this knowledge is a continuous process, this strategy is acute when the knowledge is applied toward rapid prioritization, reducing waiting time and ambiguity.

Next, the continuous strategies shifted priorities during disturbances via a mixture of *structures* and *sensemaking* practices. Paradoxically, organizations that use continuous strategies appear to exist in a constant state of change where disturbances become a form of equilibrium. Business organizations have found that *ambidexterity & organic, networked adaptation* are necessary strategies for survival. Organizations intentionally vacillate between exploitation and exploration, building adaptability and dynamic decision-making and eliminating dependence on fragile and inaccurate market forecasts. Moreover, pursuing informal networks in organizations creates organic adaptation, which is more desirable when constantly engaging disturbances (Papachroni et al., 2016b; Uhl-Bien & Arena, 2018). Also, toward continuous dynamic decision-making, people unconsciously fixate during stress and chaos. Intentional decision-makers must measure, analyze, and compare marginal gains for each action, allowing for iterative priority adjustments (Brehmer, 1992). This *cause-effect learning towards improved decision-making* helps decision-makers maintain a state of dynamic criticality. Similarly, the U.S. military continuously adapts to a rapidly changing global environment. DFE and competition continuum doctrine emphasize *adaptation by exploration* through continuous change, inserting temporal and physical randomness in force movement (DoD, 2018), and dynamic engagement levels (i.e., peacetime, cooperation, and combat operations) (DoD, 2019). This proactive strategy seeks to constantly develop new "forms" that the organization can adopt to outpace competitors, focusing on attaining an adaptive state rather than seeking specific outcomes. These strategies all target the deep development of organizational adaptive capacity, the ability to reform and reshape when faced with new challenges.

Last, the military COG analysis, RMSs, and FEMA's community lifeline support frameworks were hybrids of acute and continuous strategies. They used continuous processes to achieve dynamic criticality, but disturbances also had a clear beginning and end. The military uses COG to derive priorities from critical attributes of the environment (e.g., financial systems, physical targets) linked to the mission's desired outcome. These *nodal networks* are used for single and continuous objectives (e.g., a long campaign or operation), constantly identifying new priorities and updating old ones. COG uses a network that maps capabilities, vulnerabilities, assets, and the COGs they orbit around. The top priorities are the network attributes connected to the desired end state (i.e., the target COG). Critical priorities shift if the end state shifts (Kornatz, 2016; Perez, 2012; Schnaubelt et al., 2014). Next, *disturbance detection, adaptation identification, monitoring, and remembering* is a cyclical process that RMS and FEMA use for individual disturbances. The RMS process detects market disturbances, develops manufacturing system adaptations, and monitors market conditions' relevance. Key to this adaptation process is a rich archive of past disturbances and adaptations and the ability to recall them for reuse – simplifying future adaptation development (Khalil et al., 2020). Similarly, emergency support management applies a cyclical process for restoring essential CIs (e.g., water, electricity, shelter) after a disruption. When an incident occurs, this triggers assessments, prioritizations, logistics, and responses, a process that loops until CIs are stabilized. Emergency managers also apply their archive/remember/recall process while updating plans so that emergency response goals are relevant to the environment (DHS, 2019b).

2.5 Discussion: Infrastructure Dynamic Criticality

Having described the themes and their competencies in the results and in Figure 2, it is time to discuss how infrastructure systems can use these capabilities to practice dynamic criticality,. These themes can support infrastructure systems to detect disturbances early, pivot priorities, and balance robustness and adaptability. The thematic analysis showed that organizations that successfully confront chaos tend to engage disturbances in three phases: prior, during, and post-disturbance (FEMA, 2016). The (Park et al., 2013) framework for Sensing, Anticipating, Adapting, and Learning (SAAL) closely aligns with this process. Before chaos, infrastructure managers should probe, sense, and respond to the environment (Chester & Allenby, 2019a). The thematic analysis shows that most work toward dynamic criticality happens before chaos. In alignment with the four main themes, *goals* are set for adaptability and quick decision-making. Dynamic and flexible *structures* are formed. Organizations will practice sensemaking for past, present, and future environments and develop adaptable *strategies* to engage disturbances. Then, organizations must transition during disturbances to more acute and hybrid strategies. During disturbances, they will test sensemaking capabilities, execute plans, and rapidly innovate. After the disturbance is over and stable conditions return, organizations should shift towards expanding resilience for the future. It is time for organizations to learn, produce knowledge from the experiences, archive and remember, and change adaptations and plans for future chaos cycles. This learning component is a looped cycle that links all the other components of the adaptation process and thus deserves additional attention (Thomas et al., 2019). This final section will contextualize the themes and competencies for infrastructure, discussing them relative to the *prior*, *during*, and *post* phases of disturbance engagement. Henceforth, italicized terms refer to the framework of themes and competencies shown in Figure 2.2.

The primary takeaway from the thematic analysis is that goals toward rapid adaptability and quick decision-making are essential to building capacity for dynamic criticality. In the thematic analysis, adaptable goals focused on capabilities that enabled quick shifts in priorities. Without dynamic criticality as a goal, it is unlikely to permeate the structures and operations of the organization. Goals bring inspiration to changes in organizational structures. For example, goals to exhibit requisite complexity will inspire an organization to look for more forms that an organization can take to fit the increasing forms of the environment (Brose, 2020; C. Q. Brown, 2020; Chester & Allenby, 2022). After all, addressing complexity is about flux and unpredictability. The environment will always overcome more robust or efficient systems. So, these organizational goals, determined by leadership, will be a product of new governance that has embraced wicked complexity and uncertainty as the new normal (Chester & Allenby, 2021).

The thematic analysis indicated that, for more complex organizations, pre-established priority lists are less critical than building the capacity to engage chaos. Overemphasis on efficiency and optimization has led to rigidity and catastrophic failure in infrastructure. Leading up to the 2021 Winter Storm in Texas, electrical utility companies had neglected to upgrade system capacities and improve weatherization, resulting in an unprecedented cascading power outage and highlighting numerous areas where community resilience had been neglected (Markolf et al., 2022). Dynamic criticality thinking would have encouraged utilities to invest time in developing *loose-fit structures* and build *horizon scanning* capacity for weather-related cascading failure scenarios. With these tools, they may have had the ability to pivot priorities and develop strategies for quick reactions to extreme storms. While prioritizing assets is necessary for developing readiness and strategies to engage disturbances, static priority lists have often been mistaken as a good plan for disturbances (Clark et al., 2018). This static thinking causes shortfalls when responding to novel or extreme disturbances that exceed historical precedent (Clark et al., 2018). These shortfalls exemplify how *goals* that focus on foundational requirements (e.g., *requisite variety*, *detecting/reacting quickly*) enable adaptative *strategies* and specific competencies such as *ambidexterity*, *disturbance detection*, and *adaptation via exploration*. This adaptive capacity gives organizations more tools to confront chaos when it comes (Chester et al., 2020; B. B. Lichtenstein et al., 2007).

Capacity development for infrastructure must happen in the pre-chaos space. Adaptive capacity is not expanded during chaos as much as used (Woods, 2015). Successful organizations spend considerable effort building organizational relationships toward cultures of *sustained adaptation* and practicing reactions to chaos from the *cause-effect learning* that exercises foster. These efforts may differ depending on the type of disturbance (i.e., practicing reactions for a hurricane will look much different than practicing for reactions to seasonal monsoon flooding). Hurricane Katrina showed how neglect of pre-chaos adaptations could hamper responses. Overdependence on robustness for resilience causes infrastructure organizations to undervalue the *knowledge co-production* that comes with intentional cooperation and collaboration. There was no consensus within and between agencies about pivoting priorities when critical infrastructures failed. Organizational relationships and cooperation quickly deteriorated without firm goals and consensus methods to triage and diagnose priorities (Leavitt & Kiefer, 2006). This lesson demonstrates how prior-to-disturbance efforts to build adaptive capacity for infrastructure should focus on leadership to enable *ambidexterity*, flexible *structures*, and *knowledge co-production* necessary to bolster innovation and build capacity (A. M. Helmrich et al., 2021; A. M. Helmrich & Chester, 2022).

Reimagining infrastructures as knowledge enterprises and shifting to flexible *loose-fit* governance *structures* will grow the capacity to *adapt by exploration* much faster than traditional governance structures (Uhl-Bien & Arena, 2018). Infrastructure governance *structures* historically manifest as divisional bureaucracies, characterized by isolated divisions that often lack coordination and collaboration skillsets that may hinder many of the dynamic criticality competencies cited in this framework (Chester et al., 2020). During the Northeast Blackout of 2003, time-crucial coordination and *sensemaking* between two personnel who worked across the hallway could have prevented the cascading failure in the initial minutes of the disaster (NERC, 2004; Pescaroli & Alexander, 2016). Thus, two organizational transformations are necessary to shift toward a more adaptable paradigm. The first is to transition to a knowledge enterprise, which focuses less on developing a product (i.e., infrastructure assets) and more on developing knowledge workers (i.e., technicians, operators, and engineers) who are responsible for systems (Chester et al., 2020; Chester & Allenby, 2021). This transformation deemphasizes the importance of supervision and oversight and emphasizes leadership, empowerment, and sharing of knowledge (Davenport, 2001; Deployable Training Division, 2020), all pieces that bolster *sensemaking* and more adaptable governance *structures*. Therefore, shifting towards these principles may improve dynamic criticality via communication and coordination. Communication and coordination, in turn, increase idea syndication and expand *sensemaking* (Uhl-Bien & Arena, 2018). The second transition is to develop *ambidexterity*, switching between hierarchical and decentralized, ad-hoc *structures* during equilibrium and chaos, respectively (Chester et al., 2020; A. M. Helmrich & Chester, 2022; Siggelkow & Levinthal, 2003). These relationships also display the interconnected relationship between organizational *structures* and *sensemaking*. To this end, infrastructure organizations should practice the discomfort of shifting to emergency response teams, diverse in expertise and empowered to take quick action to *triage and diagnose* disturbances. In doing so, infrastructure organizations will familiarize themselves with scenarios where *structure* shifts are necessary, diminishing lethargic responses that may hinder dynamic criticality (Alderson et al., 2022). Furthermore, an infrastructure organization that knows when to shift between efficient and resilient structures gains the *requisite variety* to match its environment, which also aids the dynamic prioritization process (Markolf et al., 2022).

The nature of the disturbance and the outputs of *sensemaking* should guide *strategy* selection and development. Infrastructure needs to practice and exercise disturbance responses, not to be predictive, but to develop familiarity with the discomfort of surprise and intimate knowledge of the *system dynamics*. This practice expands the SAAL skillsets toward the *sensemaking* competencies of *horizon scanning* and *knowledge co-production* (Alderson et al., 2022; Ancona et al., 2020; Chester & Allenby, 2022; C. A. Miller & Munoz-Erickson, 2018). Disturbances manifested differently across the sectors of this study, and the diversity of hazards battering infrastructure appears to be doing the same. Practically, low-chaos disturbances may allow for *node-networked* responses with multiple considerations for shifting priorities – much like COG analysis, which uses critical capabilities to determine priorities dynamically. For high-chaos disturbances, reflexive reactions may be more realistic, such as *triaging and diagnosing* – much like how medical professionals sort patients into general categories during mass casualty events. Additionally, multiple strategies could be nested within each other to increase flexibility. An infrastructure control center may develop a COG-like *nodal network* based on triage-like assessments from multiple teams transmitting information, pushing back against the degradation of rationality that often occurs during dynamic decision-making (Brehmer, 1992). When chaos is so high, some organizations have no choice but to simplify the environment – as discussed in *requisite variety* (Boisot & McKelvey, 2011). But this simplification must also be balanced with proper *sensemaking*, lest infrastructure managers misdiagnose problems (Chester & Allenby, 2022). So, the nesting of strategies may be a reasonable compromise to these problems. Additionally, strategy selection may present an opportunity for human-supervised artificial intelligence systems to assist with sensemaking, reducing confusion and subjective bias while bolstering speed and agility (Markolf, Chester, & Allenby, 2021).

Although most *sensemaking* competencies should be built pre-chaos, they are tested and exercised more intensely during chaos. *Horizon scanning* and *knowledge co-production* remain essential to leading through chaos (Ancona et al., 2020) and analyzing how the chaos will affect the infrastructure system. The COVID-19 pandemic revealed that infrastructure organizations often neglect *sensemaking* to anticipate hazards (Carvalhaes et al., 2020). For example, in the summer of 2021, hospitals began to rapidly consume the available supply of liquid oxygen due to the surge in severe COVID patients. Consequently, there was concern that water utilities would run out of the resource – commonly used as a critical water treatment component (Rosen, 1973). Until the realization of resource constraints, no one had considered the interdependencies that might have caused liquid oxygen to become the critical priority for the water utility. Managers were forced to revert to simplified decision-making thresholds for water consumption and conservation (Lusk et al., 2021). But *nodal networked* thinking, *horizon scanning* as a discipline, and *disturbance detection* could have identified this vulnerability before it became a crisis. Making sense of a system requires an in-depth analysis of connections, interdependencies, and stakeholders (O'Sullivan et al., 2013). It is necessary to keep up with real-time shifts in criticality (Clark et al., 2018).

Finally, *cause-effect learning* for the future is a best practice for dynamic criticality – although it appears to be among the hardest of competencies to retain (Thomas et al., 2019; Westrum, 2006). When comparing the different sectors of this study, manufacturers appeared to do this more competently. They intentionally archive and recall previous *strategies* when a new market *disturbance is detected*. It saves time and effort in reinventing new *strategies* and helps an organization remain familiar with other competencies for adaptation to disturbances (Khalil et al., 2020). Additionally, newly developed *strategies* contribute to an ever-growing "snowball" of remembered potential responses (Sweet et al., 2014), which continue to grow *requisite variety* and contribute to a *streamlined decision-making* process. Therefore, remembering for infrastructure is foundational to requisite variety because of the interactive feedback loops between *cause-effect learning* and other aspects of *sensemaking* (Clark et al., 2019). Moreover, remembering is an essential component of organizational cognition (Cooke et al., 2013), and cognition links to *knowledge co-production* concerning systems and how responses should be tailored accordingly (C. A. Miller & Munoz-Erickson, 2018). So, infrastructure organizations must practice remembering to practice cognition, which is ultimately necessary for *sensemaking* and *strategy development* for dynamic criticality.

2.6 Conclusion

Infrastructure organizations must implement practices towards dynamic criticality during times of chaos to remain viable in rapidly changing and increasingly unpredictable environments. Other sectors provide insights into the competencies that enable rapid pivots to reprioritize knowledge and resources. Chaos is not predictable or comprehendible (Chester & Allenby, 2019a). Static priorities to engage chaos will remain unknowable, much like an "event horizon of chaos" for infrastructure. Thus, the results of this study show that if infrastructure organizations wish to approach dynamic criticality amidst disturbances, they should focus on maximizing adaptive capacity. Specifically, during periods of equilibrium, they should set goals for rapid adaptation and quick decision-making. They should alter their formal structures in ways that are friendly to sustained adaptation, which can be dynamic, flexible, and shiftable when disturbances occur. These goals and structures will then enable sensemaking competencies, allowing the organizations to scan the horizon for threats and make sense of increasing information flow (before, during, and after disturbances). These efforts will give way to the final sought-after product: practical strategies for dynamic criticality. Beneficial future research may be the historical analysis of disturbances and how dynamic criticality was or was not achieved by infrastructure organizations. But care must be taken not to develop specific decision-making frameworks, as they may lead to strategy entrenchment and a decrease in adaptive capacity. The primary lesson from this work is that strategies are also dynamic and unique to disturbances. Thus, focusing on adaptive capacity will benefit infrastructure organizations more than a rigid list of priorities.

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CHAPTER 3

PREPARING INFRASTRUCTURE FOR SURPRISE: FUSING SYNTHETIC NETWORKS, INTERDEPENDENCY, AND CASCADING FAILURE MODELS

3.1 Introduction

There is a pressing need to understand fine-scale infrastructure dynamics of how disturbances occur. Infrastructure managers often lack insight into how interdependent networks interact and affect each other when failures are triggered (Chester & Allenby, 2019a; FERC & NERC, 2012; Leavitt & Kiefer, 2006; Mitsova, 2021; Vespignani, 2010). Limited vision into how failures occur is accentuated by rapidly changing conditions in local and global environments (i.e., the Anthropocene, as defined by Lewis and Maslin, 2015; Steffen et al., 2015)) which are increasingly subjecting infrastructure to hazards that exceed design conditions (B. Allenby & Chester, 2018; Markolf, Chester, Helmrich, et al., 2021). The accretion of new technologies, climate change, and increasing interdependencies within and across infrastructure are introducing novel cascading failure scenarios (Arbesman, 2016; Vespignani, 2010). Increasingly, small, localized outages initiate large cascading failure events (Ganin et al., 2016; Zorn et al., 2020). They are usually preceded by the confluence of unlikely factors leading to an extreme outcome (i.e., perfect storms) or are high-impact events that were unforeseen or unimagined (i.e., black swans) (Paté-Cornell, 2012; Taleb, 2007). In response to this increasing complexity, infrastructure managers require new models and methods to systematically search for weak signals that probe for new destabilizing conditions (i.e., horizon scanning) (Chester & Allenby, 2022).

Horizon scanning requires continued investment toward understanding system dynamics and novel disruptors (Chester & Allenby, 2022; Iwaniec et al., 2020; Muñoz-Erickson et al., 2021). Generally, a single infrastructure's engineering design, construction, and dynamics are well understood. However, there is a limited understanding of how infrastructure dynamically interacts with other systems (Chester & Allenby, 2019a). Infrastructure risk analysis models have historically failed to fill this gap (Buldyrev et al., 2010; Hasan & Foliente, 2015). Thus, researchers have developed bodies of literature to study infrastructure interdependency (Mahabadi et al., 2021; Ouyang, 2014) and cascading failure (J. Li et al., 2019; Valdez et al., 2020). These fields generally seek to identify trending behavior and propose changes to repel and resist disturbances and failures (i.e., resilience).

Unfortunately, data availability and low stakeholder participation remain persistent barriers to improving interdependency and cascading failure models (Cantelmi et al., 2021; Ouyang, 2014). In place of data to build models of *real networks* (Figure 3.1), cascading failure and interdependency models are forced to use benchmark networks like IEEE networks (Mohammadi & Saleh, 2021) or virtual city networks like *Micropolis* (Balakrishnan & Cassottana, 2022). But these theoretical networks (Figure 3.1) lack the realistic detail needed for new design algorithms and risk analysis of future scenarios like extreme climate events (Bachmann et al., 2020; Marcos et al., 2017; Paté-Cornell, 2012). Novel models are needed to aid resilience efforts.

In response to the need for detailed data, infrastructure sectors are beginning to develop *Synthetic Networks* (Figure 3.1)*:* fictional but realistic models of networks that imitate the appearance and behavior of real-world networks (Marcos et al., 2017). These networks can serve as platforms for diverse and enhanced urban infrastructure analysis. Realistic synthetic networks generally need to have three properties: the representativeness of existing networks, the confidentiality of real-world data, and the use of real engineering properties (Mohammadi & Saleh, 2021). Methodologies and validation of these models are developing, and no established framework or vision is identified in the literature for how synthetic networks should be deployed for resilience research.

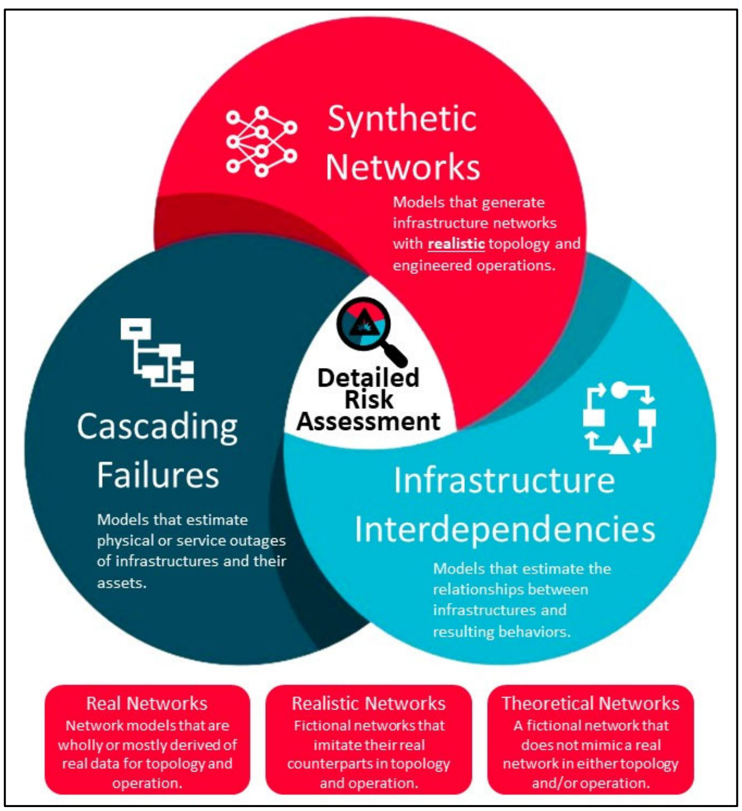

Figure 3.1 – Fusion of Synthetic Interdependent Cascading Failure Models (SICFMs)

This paper seeks to advance the vision for infrastructure resilience and risk analysis modeling. This chapter proposes that unique and critical insights exist at the intersection of the three modeling domains of Synthetic Networks, Interdependency Modeling, and Cascading Failure models (Figure 3.1). This intersection is referred to as Synthetic, Interdependent, Cascading Failure Models (SICFMs). Because detailed data continues to challenge interdependency and cascading failure research (Ouyang, 2014; Valdez et al., 2020), SICFMs may provide the fine-scale analysis necessary to elucidate novel scenarios like *black swans* or aid in unearthing new solutions for wicked complex problems. Thus, this paper will explore modeling possibilities for SICFMs. This chapter aims to identify practical uses for fine-scale synthetic models combined with interdependency and cascading failures.

Toward identifying a framework of SICFMs, a state of practice will be conducted for the three research domains. It is necessary to understand procedures, methodologies, capabilities, and limitations for each domain. This state of practice will be focused on literature that uses at least one of the domains. As this study is concerned with modeling and resilience analysis for urban physical infrastructure, the literature search will focus on studies that use geospatial analysis in the model. The literature analysis will focus on physical infrastructure (e.g., power, water, road transportation), referred to as "civil infrastructure" throughout the text. Reviews already exist for the individual domains, and this chapter will utilize this knowledge base (Bachmann et al., 2020; Banerjee et al., 2014; Guo et al., 2017; Mahabadi et al., 2021; Marcos et al., 2017; Mohammadi & Saleh, 2021; Ouyang, 2014; Valdez et al., 2020; Wei et al., 2019). Following the state of practice, a framework for SICFMs will be developed, and the capabilities from each domain will be synthetized to propose how future SICFMs can be deployed.

3.2 State of Practice

The three domains in this study are at different stages of research maturity. Synthetic network research is younger than interdependency and cascading failure. However, synthetic studies have recently increased in publication. Interdependency research is rooted in physics and mathematical relationships between theoretical networks but is now applied to study real networks. Similarly, cascading failure research began in the physical sciences using theoretical models but increasingly uses engineering models to simulate failures. Interdependency and cascading failure models often lack detailed information about their networks. This gap appears to be a primary motivation for realistic synthetic network development. Academic search databases, Google Scholar, Web of Science, Scopus, and ASCE libraries were used. Keyword searches included combinations of the terms "infrastructure," "cascading," "failure," "interdependent," "network," and "synthetic." Seventy-six peer-reviewed research publications were identified and analyzed. In addition to the research publications, 18 academic review papers from 2010 to 2022 were included. The state of practice will present general observations about infrastructure network modeling and current practices for synthetic networks, interdependencies, and cascading failure.

3.2.1 General Infrastructure Network Modeling State of Practice

Three archetypical network structures were identified in the literature: theoretical, real, and synthetic, as already introduced in Figure 3.1. The archetypes frame the models for infrastructure interdependencies and cascading failures. Theoretical networks generally do not mimic a real infrastructure network topology or operation. Rather, they are specifically designed to experiment with interdependencies between multiple networks or to test topology robustness considering cascading failure to inform future real network design (Y. Wu et al., 2021; C. Zhang et al., 2020). Real networks use actual network data – often redacted – to study specific components or attributes of infrastructure to identify component criticality, resilience, or vulnerabilities. These models can give prescriptive recommendations to practitioners for maintenance, asset management, or hardening requirements (Abdel-Mottaleb et al., 2019; Dong, Wang, et al., 2020; Zorn et al., 2020). In contrast, synthetic network models are realistic but fictional networks. Often used for power infrastructure, synthetic networks are being developed to provide realistic test cases for future network optimization and emerging technologies such as microgrids and decentralized renewable generation (H. Li et al., 2020; Marcos et al., 2017; Meyur et al., 2022). Theoretical and real networks were primarily used for interdependency studies and cascading failure simulations, whereas most literature on synthetic networks still focuses on model development (Marcos *et al.*, 2017).

The three domains have researched many different infrastructures but tend to focus on power, water, communications, transportation, and energy. Power was the most common and contained both transmission and distribution studies. Water primarily focused on network constructs, component criticality, and dependency on power infrastructure. Studies involving communications tended to focus on co-dependency with power and SCADA. Energy infrastructure (non-power), which refers primarily to fossil fuels (e.g., oil and natural gas), also focuses heavily on interdependencies with power.

Finally, road and other transportation studies focused on interdependencies with communications networks, storm, water, sewer, and power.

3.2.2 Synthetic Infrastructure Networks

The development of realistic dynamic simulation methodologies for infrastructure has revealed a dearth of realistic networks to test these methodologies (Marcos et al., 2017). Thus, synthetic networks are being developed and validated as realistic representations of their real infrastructure network counterparts. While some public data are often foundationally used, synthetic networks must function primarily without being informed by real network properties. They must also use engineering design for construction and operation (Mohammadi & Saleh, 2021). Naturally, the unique functions of different infrastructures will have varying requirements to build a synthetic network. For example, transportation infrastructure has well-documented network topology with well-established models for traffic flow dynamics. This access to topology makes it easy to model the structure and simulate functions. In contrast, power infrastructure organizations do not generally release topology to the public; however, their operations are generally understood and can be engineered in models. So, unlike transportation, it is easy to model the operations of a power network but difficult to know how topology and design should imitate the real world. From 2015 to 2022, synthetic research has produced a small body of literature that has focused chiefly on methodologies for network development with some emphasis on operations. But their practical uses for interdependency or cascading failure simulations are beginning to emerge.

Synthetic power models are the most developed of civil infrastructure. Mohammadi and Saleh (2021) completed the first systematic review of synthetic power models. Transmission models have advanced separately and faster than distribution models. Many transmission test networks, their datasets, and some open-source models are publicly available, but no convenient software platforms have been released. Additionally, studies have yet to automate the network creation process for transmission or distribution. Some expert design with manual input is still required.

Synthetic transmission power models commonly use population data to estimate large-scale loads (Gegner et al., 2016) and contingency and sensitivity analysis to balance the model for realistic responses to demand fluctuations (Birchfield et al., 2019; Birchfield & Overbye, 2020). Realistic topology is particularly challenging for synthetic transmission networks because the lines often cut across geographical features or do not follow other urban features such as roads. Thus, models often use economic and technical optimization to design transmission network topology (Espejo et al., 2019). This topology construction is sometimes aided by Delaunay triangulation and "minimum spanning tree," a geometrical optimization method. Transmission line edges – covering more considerable distances – are mapped in a "line of sight" direction from node to node (Mohammadi & Saleh, 2021).

Synthetic power distribution models have kept pace with synthetic transmission models. Typically, distribution network edges are assumed to follow road topology from open-source street data (Mohammadi & Saleh, 2021). Synthetic distribution feeders have been synthesized using generalized census data for small-grid test cases (Saha et al., 2019), allowing for detailed, realistic grid monitoring in power flow simulators. Ali et al. (2022) incorporated customer-level power data with demand for every facility in the distribution area. They used a validation methodology that included a review from industry experts at a local utility company. Notably, the researchers had access to detailed demand data – which deviates slightly from the tradition of synthetic models using public-only data. In partnership with NREL, Mateo et al. (2020) created "RNM-US," a methodology to synthesize power distribution networks for large areas in the United States. Meyur et al. (2022) created a synthetic distribution model using publicly available data in combination with engineering and economic optimization. The simultaneous emergence of various synthetic transmission and distribution models bodes well for the future of synthetic power research. Ideally, merging best practices will unify research efforts as methodologies are refined.

Combining synthetic transmission and distribution networks was only identified once in the literature. Li et al. (2020) combined a synthetic power distribution grid model created by the RNM-US model (Mateo et al., 2020) with existing synthetic transmission methodologies (Birchfield et al., 2017; Gegner et al., 2016) to develop a realistic and cross-scale synthetic power grid for the entire state of Texas. The methodology was validated using utility-provided metadata.

Water distribution models have received some synthetic methodology development. DynaVIBe was one of the earliest attempts to synthesize water networks (Sitzenfrei et al., 2010). The model used roads to create a realistic topology with simplified demand estimations. The authors later improved their loop methodology to reduce unnecessary redundancies (Mair et al., 2014). Then, using an Integrated Urban Water Management Model (IUWM) by Sharvelle et al. (2017) to estimate small-scale demand, Ahmad et al. (2020) automated the hydrology design in EPAnet using minimum spanning tree topology, resulting in a model that realistically imitated the Phoenix Metro

Region. More recently, a synthetic dynamic water flow framework was developed in a multi-infrastructure synthetic study by Wang et al. (2022). Instead of focusing on realistic network generation, they used existing synthetic networks to develop a methodology for dynamic flow throughout the water network and between the other networks. Momeni et al. (2023) designed an iterative WDN synthetic network generator. They used standard design criteria to govern network creation and used resilience and cost constraints as optimization factors.

The remaining infrastructure types that included synthetic networks were road transportation, communications, energy, stormwater, and buildings. Synthetic development appears nascent for these sectors. Most research for transportation infrastructure focuses on road networks (Mohebbi et al., 2020). Road topology is well documented with publicly accessible data, eliminating the need for synthesizing. Additionally, existing dynamic traffic flow models are abundant, but they have significant theoretical components because of the agent-based nature of traffic flow (Dong et al., 2020). As such, they are not "synthetic" in the same ways as, for example, power or water. Thus, the characteristics of synthetic networks may vary across infrastructure domains. Despite these differences, other infrastructure models share a goal of re-creating realistic behavior. For example, a synthetic road model was coupled with synthetic stormwater to analyze resilience during intense storms and floods. The geographic and physical interdependencies revealed more realistic responses for the two infrastructures that would have been latent in single-network analysis (Y. Yang et al., 2019). Moreover, in a later study, the same authors added variance to storm sewer component conditions for nuance and realistic behavior (Y. Yang et al., 2020).

Additionally, Wang et al. (2022) modeled dynamic exchanges of resources within and between natural gas, power, and water networks instead of static or binary interdependencies. Two studies created synthetic communication networks and paired them with synthetic power grids. In both cases, the communication network topology was based on the power topology. Additionally, network operation was calculated stochastically instead of using realistic engineering parameters (Fu et al., 2022; Korkali et al., 2017).

Validation methodologies for synthetic networks appear primarily for power and water. Most commonly, models use metadata from real-world infrastructure counterparts to validate topology (Espejo et al., 2019; H. Li et al., 2020; Sitzenfrei et al., 2010). Some real-world test datasets may be compared to model topology and functionality. Ahmad et al. (2020) followed this validation method for synthetic water models by testing topology and operation against a publicly available small-town water distribution network. Similarly, Meyur et al. (2020) obtained a small subset of real-world data within their study region and compared topology and network performance to their model for validation. Synthetic power network operational validation is improved by analyzing voltage variability across time to test realistic behaviors (Idehen et al., 2020). Additionally, the water and power research communities have provided open-source test sets that researchers may use to improve methodologies. But, test cases have significant real-world limitations in their realism (Marcos et al., 2017). So, while test cases may be helpful for development, the validation process still requires some real-world data (Mohammadi & Saleh, 2021; Sitzenfrei et al., 2010). One model for synthetic power distribution used industrial validation, sending the model and data output to the utility provider from the region of study. The utility provider analyzed and compared the model to the real-world network without compromising security and then provided feedback to the research team (Ali et al., 2022). Using industrial experts seemed to be the most robust validation method, but stakeholder participation may be a barrier for different locations.

As progress continues in developing realistic infrastructure models, researchers have begun to couple different infrastructure types together. Wang, Yu, and Baroud (2022) combined synthetic power, water, and gas to investigate interdependent relationships during flow variations. As already mentioned, Yang et al. (2019, 2020) coupled stormwater and road transportation. But, thus far, these are the only two studies with coupled synthetic networks.

Synthetic network model development is still nascent for most infrastructure. The power research community has recognized the need to develop robust synthetic methodologies (Marcos et al., 2017; Mohammadi & Saleh, 2021). Some water models have been developed but are still emerging, and other infrastructure disciplines appear to be focused elsewhere. Synthetic network development for multiple infrastructures may aid interdependency modeling (Marcos et al., 2017), and a few synthetic studies attempt to couple multiple infrastructures (Yang et al., 2019; Yang et al., 2020; Wang, Yu and Baroud, 2022). More work is needed to develop other infrastructure methodologies. The need for a greater understanding of interdependencies may motivate the acceleration of synthetic development in other infrastructure disciplines.

3.2.3 Infrastructure Interdependence

Interdependency research is the study of interactions between mutually reliant infrastructures. Usually, these studies involve reactions to disturbances (J. Li et al., 2019).

It is more mature than the synthetic infrastructure domain but still needs major progress for models to be useful in the real world (Banerjee et al., 2014). The events of 9-11 accelerated awareness of the urgent need for increased infrastructure security and how infrastructures interact and are accessed and affected via multiple mediums. Thus, interdependency research seeks to inform the design and management of various infrastructures (Pederson et al., 2006; Rinaldi et al., 2001). For example, urban fires can cause failures in power infrastructure, which cuts power to water pumps, hampers firefighting capabilities, and simultaneously deprives power plants of cooling water, leading to more power outages (Bagchi et al., 2010). Large urban disturbances often congest roads and lead to cascading feedback loops between transportation and communication (Barrett et al., 2010). Terrorist attacks can disable coupled energy infrastructure like power and gas (B. Wu et al., 2016). Earthquakes can simultaneously disable power and communication, adding confusion and complexity to response efforts (Cardoni et al., 2020) and can cause further interdependent losses to critical infrastructure like water and gas (Cárdenas et al., 2022). Also noteworthy, interdependencies between environmental and technological factors can quietly amplify social vulnerabilities and inequalities (Wakhungu et al., 2021). To discuss the state of practice for interdependency research, this section will briefly overview the evolution of interdependent models. A generalized discussion of methodologies to study interdependencies will follow. This section concludes with ongoing challenges and paths forward.

The infrastructure community recognizes four general types of infrastructure interdependencies Rinaldi et al. (2001): i) physical (a direct link between two networks where inputs and outputs directly affect each other), ii) geographic (co-location such that a local event can create a mutual state change), iii) cyber (relying on communications infrastructure and its dataflows for proper function), and iv) logical (mutual reliance via a means that is not physical, geographic, or cyber-related, e.g., financial). Many physical interdependency studies focused on the nexus of water and energy (Bagchi et al., 2010; Balakrishnan & Cassottana, 2022; Cárdenas et al., 2022; Heracleous et al., 2017; Holden et al., 2013; Kong et al., 2019; Min et al., 2007; Munikoti et al., 2021; Sharma & Gardoni, 2022; K. Wang et al., 2022; Yin et al., 2022; Zorn et al., 2020). Geographic interdependencies were also common in real network analysis, likely because realistic geospatial data were available. Multiple studies examined the interdependencies between power and communications. Still, many of them recognize that the modeling logic used between the power-cyber nodes may be more representative of a physical interdependency than a cyber interdependency (Buldyrev et al., 2010; Eusgeld et al., 2011; Fu et al., 2022; Heracleous et al., 2017; Kalstad & Wolthusen, 2007; Kong et al., 2019; Korkali et al., 2017; Liu et al., 2019; Min et al., 2007; Nan & Sansavini, 2017; Ramachandran et al., 2015; Rueda & Calle, 2017; P. Zhang & Peeta, 2014; Zorn et al., 2020). Some studies used logical interdependence to represent human factors such as demand (Heracleous et al., 2017) or the behavioral relationships between traffic and cellular network congestion (Barrett et al., 2010).

The first interdependency models were developed by mathematicians and physicists but eventually became an interdisciplinary field (Pederson et al., 2006; Satumtira & Dueñas-Osorio, 2010). Following the seminal definition of interdependencies by Rinaldi et al. (2001), the first numerical studies focused on the behavior of non-specific interdependent networks (Eusgeld et al., 2011). These initial models used networks with simple node and edge structures. They also had binary interdependency relationships and randomized disturbances that were less realistic (Ganin et al., 2016; Holden et al., 2013; Kalstad & Wolthusen, 2007). These confirmed the theory that interdependencies could often lead to more severe cascades and thus deserve greater attention. Satumtira & Dueñas-Osorio (2010) reviewed studies of interdependency and confirmed at the time that current models were too rudimentary and recommended the development of dynamic models with realistic engineering principles. Models also needed to be developed for practitioners and commercial use to make interdependency study more accessible (Pederson et al., 2006; Satumtira & Dueñas-Osorio, 2010). Subsequently, more studies focused on practical applications, asking questions about how interdependence affects infrastructure. Shen (2013) coupled an IEEE test case power model and a random network to simulate interdependence with SCADA and optimized interconnections by minimizing construction and repair time when disturbances were introduced. They concluded that simplified network interdependency was inadequate for optimizing infrastructure network construction. Nan & Sansavini (2015) focused on interactions between Switzerland's simplified power transmission, associated communication networks, and stochastic human operator decisions during disturbances. They used these interactions to find how interdependence and operator decision-making affected power resilience. Most recently, interdependence modeling has come from theoretical and practical applications (Sharma & Gardoni, 2022). Theoretical models are rooted in physics, seeking broadly applicable virtues of interdependency, while practical models employ engineering design principles to answer specific resilience questions (Buldyrev et al., 2010; Mahabadi et al., 2021). Practical models have struggled to emerge in the absence of real-world data. Stakeholder participation is needed to improve understanding of real interdependencies to make the models more realistic (Mitsova, 2021; Suo et al., 2021).

Methodologies for interdependency generally revolve around feedback between networks, stochastic factors, topology (i.e., the shape of the network), and node and edge criticality (Abdel-Mottaleb et al., 2019; Bachmann et al., 2020; Schweikert et al., 2021). Graph and network theory are long-time accepted methods for representation and analysis (Satumtira & Dueñas-Osorio, 2010). Interdependency studies can model feedback between the networks bilaterally or unilaterally. Bilateral modeling simulates dynamic exchanges between infrastructure networks but is computationally expensive and can be complicated to synchronize temporally. Unilateral representations lose some dynamic realism, but researchers try to balance this loss with stochastic variables. Both feedback methodologies are currently used (Sharma & Gardoni, 2022). Additionally, stochastic factors are used in other ways to increase realism. For example, some components may deteriorate over time, affecting the probability of spontaneous and interdependent failures (Bondank, Chester, and Ruddell, 2018; Yang et al., 2020). Another example is Zhou et al. (2022), who stochastically represented dynamic response prioritization based on node and edge criticality. They found that this prioritization improves long-term network performance. Studies focusing on topology construct usually seek distinctive physical traits of the more resilient networks. The hope is that these unique traits may correlate to real-world resilience (Dueñas-Osorio & Vemuru, 2009). Results have been mixed on whether interdependency generally aides or hampers robustness. Wang et al. (2018) found that interdependency sometimes caused a decrease in robustness during targeted attacks on crucial nodes. Similarly, Zorn et al. (2020) found that sympathetic failures tended to spill across networks when interdependence was high. But context is important in these conclusions. When networks had asymmetric interdependent connections, the network was more resistant to cascading failure (Liu et al., 2019). Also, Korkali et al. (2017) compared two models, one with simple feedback between networks and the other with more realistic and complex feedback. They found that in the realistic model, robustness increased as interdependency increased. But the inverse was true for simple networks. So there is no firm conclusion regarding topology construct and robustness. Similar to topology research, other studies have investigated node and edge criticality for network resilience. In these models, highly connected nodes are bottlenecks. Munikoti et al. (2021) found that outages involving critical nodes were more destabilizing to multi-network models. Ouyang (2016) had similar results for node criticality but also found that edge criticality was not as impactful on resilience. Overall, interdependency research has standards for methodologies, but the interdisciplinary nature of this field implies that there will be variance in how models are constructed.

Some studies focus on the role of interdependencies in real-world events. These studies often use case studies investigating the practical dynamics of disturbance-related interdependence in real-world infrastructure. Krishnamurthy et al. (2016) did an in-depth case-study on power and communications interdependencies after earthquakes in Japan and Chile. They found that power is not only dependent on communications for SCADA operation, but coordination of response and repair teams also relies on communication infrastructure, significantly affecting operations and recovery for both systems. These dynamics imply that more continuous exchanges between these two networks may be necessary for interdependent studies that model continuous cascades (Varga et al., 2014). Another study used historical outage data from Hurricane Hermine to train a statistical model, predicting road closures and power outages (Madhavi et al., 2019). They used the model for predictions of failure in future storms. The study of real data from past events may help inform how interdependencies should be modeled in the future and is necessary to improve models (Bachmann et al., 2020).

There are three primary research gaps for infrastructure interdependence, according to Haggag et al. (2020): i) resilience quantification, ii) defining interdependence, and iii) modeling of real-life systems. These issues are rooted in several shortfalls. First, models have computational limitations. They cannot account for all spatial and temporal factors; there is tension between the accuracy of models and the time and cost to produce and run them. Second, researchers have limited access to or cannot collect data to study and mimic real-world infrastructure. Thus, researchers are forced to narrow their questions.

Interdependency research is a broad and interdisciplinary field. The focus is primarily on power, water, communications, and transportation. Other civil infrastructures are not as developed. Non-technological critical infrastructure (e.g., medical, agriculture, logistics) has yet to be included in interdependency research. Physics and mathematics-based methods have successfully unearthed macro-behaviors. Detailed models seek to elucidate more nuanced behaviors, but these are slow to emerge.

3.2.4 Infrastructure Cascading Failure

Cascading failure modeling is a prominent subfield of infrastructure research. Cascading failure models have been applied to many infrastructures, evaluating failure behaviors and recovery strategies. Cascading failure models have two primary approaches. The first is to capture reactions to *progressive failure.* This method tests robustness by progressively removing nodes and edges and often foregoes detailed engineering functions within the physical and operational model (Mahabadi et al., 2021). The other approach, *dynamic failure*, introduces an initial disturbance and uses engineering operations combined with stochastic variables to simulate responses within the model (Y. Wu et al., 2021). These models are often complex and computationally expensive (Valdez et al., 2020). Cascading failure models are used for the general purposes of 1) resilience framework development; 2) topology evaluation, 3) identifying component criticality; 4) seeking thresholds for total collapse, and 5) supporting interdependency model development. Within these uses, some models focus only on cascading failure, while others expand the model to simulate post-disturbance recovery. Methods and uses are discussed in this section, followed by a brief overview of which infrastructures have been included in cascading failure models.

Some research efforts develop models to evaluate the resilience of real-world networks. These studies use theoretical test networks to simulate *dynamic failure* and observe behaviors to derive evaluation metrics. These metrics form the basis for a framework, which can then be used to evaluate other infrastructure networks for resilience. Oftentimes, the studies will use a second test network to validate the framework (Bagchi et al., 2010; Balakrishnan & Cassottana, 2022; Cárdenas et al., 2022; Cardoni et al., 2020; Guidotti et al., 2016; Kong et al., 2019; Korkali et al., 2017; Munikoti et al., 2021; Nan & Sansavini, 2017; Oughton et al., 2019; Sharma & Gardoni, 2022; Thacker et al., 2017; B. Wu et al., 2016; B. Yang et al., 2020; Y. Yang et al., 2019; Zorn et al., 2020).

A body of work focuses on the resilience of different network topologies when subjected to disturbances (Azzolin et al., 2018; Berardi et al., 2014; Buldyrev et al., 2010; Dueñas-Osorio & Vemuru, 2009; Korkali et al., 2017; Liu et al., 2019; K. Wang et al., 2022; Y. Wu et al., 2021; C. Zhang et al., 2020). For example, cascading failures were used to optimize topology for a coupled power and gas model in Harris County, Texas, by changing the network characteristics (Ouyang & Dueñas-Osorio, 2011). Additionally, Dueñas-Osorio & Vemuru (2009) modeled cascading failure in a simple power network and found that a strategic combination of intentional redundancy and islanding via weak links decreased failures.

Cascading failure models are used to identify critical components of single and multi-network models (Abdel-Mottaleb & Zhang, 2020; Berardi et al., 2014; Buldyrev et al., 2010; Dueñas-Osorio & Vemuru, 2009; Ouyang, 2016; Schweikert et al., 2021; S. Wang et al., 2018, 2019; C. Zhang et al., 2020; J. Zhou et al., 2022). For a single network model, a power grid study might focus only on critical nodes and edges (Dueñas-Osorio & Vemuru, 2009). Conversely, a water-road model might consider the water network's service level and how the road network may flood when a water pipe bursts (Abdel-Mottaleb & Zhang, 2020). These models typically use *dynamic failure* simulations.

The possibility of total collapse when key tipping points are reached is another area of focus. These studies typically use *progressive failure* approaches with simple networks and interdependent relationships. They progressively and randomly fail nodes and edges until the entire network collapses (Mahabadi et al., 2021). Networks will often continue to function despite initial outages but reach a transition point where collapse occurs very quickly. A single- or multi-network model is considered more robust if the transition point occurs late in the failure process, indicating that the network can withstand more failures before the collapse suddenly accelerates (Barrett et al., 2010; Dong, Mostafizi, et al., 2020; Dong, Wang, et al., 2020; Liu et al., 2018; Pahwa et al., 2015).

In some cases, cascading failure models are often used within other models that focus on the dynamics of infrastructure interdependencies. In these cases, failure is generally not the focus but, instead, how failures affect dynamics and exchanges between the modeled networks (Heracleous et al., 2017; Holden et al., 2013; K. Wang et al., 2022; Yin et al., 2022).

Cascading failure models are generally focused on the vulnerabilities of infrastructure (Mahabadi et al., 2021; Meyur, 2022), but some studies also focus on recovery from disturbances. (Barrett et al., 2010; Guidotti et al., 2016; Holden et al., 2013; Munikoti et al., 2021; Nan & Sansavini, 2017; Sharma & Gardoni, 2022; Shen, 2013; Y. Yang et al., 2019). For example, Sharma & Gardoni, (2022) modeled power-water recovery after an earthquake to estimate recovery times for Tennessee emergency management response plans. Recovery from cascading failure is also modeled to test disturbance response strategies. Kong et al. (2019) found that prioritizing path-dependent (i.e., more connected) assets during recovery minimized restoration times for the overall system of interdependent networks. Also, recovery modeling can test how maintenance strategies for components will change how networks fail and recover from outages, helping infrastructure managers seek an optimal return on investment (K. Wang et al., 2022).

There is a notable absence of research on *perfect storms* and *black swans* in cascading failure research. Many cascading failure models simulate failure until total collapse. But the subsequent analysis tends to focus on generalized behaviors, avoiding low-probability-high-impact outcomes. Previous literature has pointed out that cascading failure models and risk assessment tools have been historically inadequate for analyzing black swans (Aven, 2013; Hasan & Foliente, 2015; Paté-Cornell, 2012), and this appears still to be true.

Cascading failure has been studied across many infrastructures, such as electricity, energy, water, stormwater, sewer, and transportation. Power is the most studied infrastructure (Pagani & Aiello, 2013). Studies that focused solely on electricity investigated questions around ideal network topologies and sought to understand the dynamics of outages in transmission and distribution. These studies have recommended topology changes to decrease cascading failure (Azzolin et al., 2018; Dueñas-Osorio & Vemuru, 2009). Dueñas-Osorio & Vemuru (2009) used *dynamic failures* to recommend topology changes involving "weak links" in the transmission network. As a result, service areas would be naturally islanded from specific line failures during outages, protecting the remaining network. Others used *progressive failures* to estimate total collapse thresholds. They found that larger networks are more at risk of catastrophic blackouts and prescribed methods for intentional islanding during disturbances (Pahwa et al., 2015). For water, mechanical component failure is often the cause of cascading failures. Berardi et al., (2014) used *dynamic failure* to determine the criticality of components. They found that prioritizing preventive maintenance by criticality rather than component age reduced cascade severity. For roads, Dong et al., (2020) *progressively failed* random portions of the road network to estimate the critical point at which Portland's transportation infrastructure transitioned to total collapse. These single-network studies bring critical insight into how cascades occur. But there is also a growing need to study and quantify how failures in one network may also affect other networks (Rinaldi et al., 2001).

Models of cascading failure involving multiple interdependent infrastructures have begun to appear in recent years. Power networks appear most frequently and are often paired with water distribution, communications, and non-electrical energy (e.g., oil and natural gas) infrastructure (Haggag et al., 2020). These models are frequently used to elucidate how interdependent relationships affect cascading failure (Zorn et al., 2020). Power-water cascading failure is a topic of interest due to their high interdependence in the face of rising global temperatures (Bagchi et al., 2010; Balakrishnan & Cassottana, 2022; Bartos & Chester, 2014; Clark et al., 2019). Power and communications network cascading failure is also commonly examined due to the inseparable nature of power and SCADA and the associated risks of catastrophic outages (Korkali et al., 2017; Krishnamurthy et al., 2016; Liu et al., 2019). Power and other energy infrastructure are often paired due to the economic impact of power failures that may affect oil and gas production and distribution (Ouyang, 2016; Ouyang & Dueñas-Osorio, 2011; S. Wang et al., 2018; B. Wu et al., 2016). Abdel-Mottaleb & Zhang (2020) paired water-road networks to inform water component maintenance priorities based on how water pipe failures degraded road transportation. In an exceptional case, Zorn et al., (2020) created cascading failure model for ten interdependent infrastructure networks. But their results were necessarily more granular than models with only two or three infrastructures.

3.3 Discussion: A Framework for the Future of SICFMs

This section fuses the three domains to propose a framework for SICFMs. Synthetic networks are detailed and realistic enough to serve as a modeling foundation. However, SICFMs need synthetic networks to reach a viable point of development before being deployed. SICFMs will also need expanded interdisciplinary stakeholder support to ensure that the specialized facets of the model are robust and continuously validated. Researchers should balance automated modeling with expert design to maximize deployability and realism. SICFMs should employ dynamic interdependencies for coupled networks, expanding opportunities for cyber and logical interdependencies. With these new developments, SICFMs should incorporate other non-technological factors to tie cascading failures back to human capabilities. These improvements should provide novel opportunities for fine-scale risk analysis to scan the horizon for surprise events (i.e., perfect storms and black swans). These recommendations are summarized and shown in Figure 3.2.

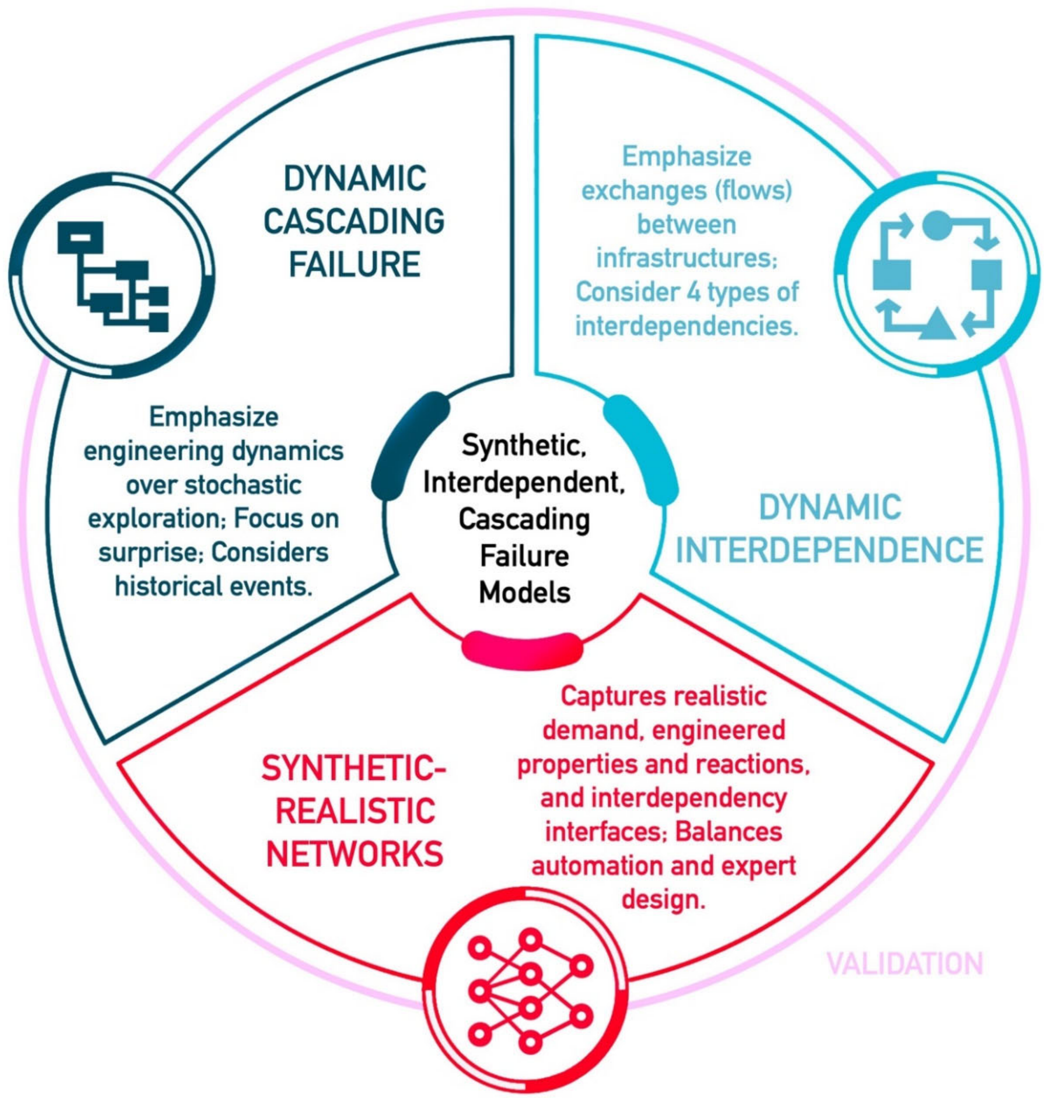

Figure 3.2 – Resulting Framework for SICFMs.

Synthetic network methodologies should strive to meet two requirements before deployment in SICFMs. First, the methodology should be usable across many geographic locations (Mohammadi & Saleh, 2021)(Mateo et al., 2020). Second, the method must withstand rigorous validation (Ali et al., 2022; Birchfield et al., 2017; Idehen et al., 2020; Krishnan et al., 2020; Mohammadi & Saleh, 2021). Synthetic power models can currently produce highly detailed transmission and distribution networks in nearly any location in the United States and Europe (Ali et al., 2022; Birchfield et al., 2019; Birchfield &

Overbye, 2020; Gegner et al., 2016; H. Li et al., 2020; Mateo et al., 2020; Saha et al., 2019). Thus, power networks appear mature enough to be deployed for SICFMs. Water models have been developed, and some are applicable in many geographic regions, but further validation of current methodologies is needed (Ahmad et al., 2020; Momeni et al., 2023). Some synthetic networks exist for other energy, transportation, and communication, but only water and power methodologies have been explicitly developed with multiple research papers. More work is needed to bring other infrastructure to the same level of development as power and water.

This need also reveals an ongoing challenge for SICFM development. SICFMs come from interdisciplinary research. But interdisciplinary researchers seeking to develop SICFMs may not have the expertise to engineer synthetic networks for specific infrastructures. In the state of practice, synthetic network development comes from research experts in an infrastructure field, prompting two recommendations. First, stakeholder partnerships should be expanded across research fields to foster synthetic development (Cantelmi et al., 2021; Hasan & Foliente, 2015). Second, synthetic networks should be designed for easy access by the broader research community, and expert designers should structure synthetic models so interdisciplinary researchers can integrate them into SICFMs (Marcos et al., 2017; Mohammadi & Saleh, 2021).

Notably, research for synthetic power has exemplified how to blend automation with expert design during crucial parts of the modeling process (H. Li et al., 2020; Mohammadi & Saleh, 2021). Expert design may not be as fast as automated procedures. However, an expert engineer is capable of specifying important details during the modeling process. This nuance is necessary for risk analysis for surprise events (Paté-

Cornell, 2012), further emphasizing that broad stakeholder participation is vital for developing SICFMs (Hasan & Foliente, 2015).

Additionally, synthetic models are engineered to react *dynamically* to changes in supply and demand (Gegner et al., 2016), so they should also be engineered with points of connection for interdependencies with other infrastructure. These connections would allow synthetic models to react not only to the direct impacts of hazards but also to unexpected changes in interdependency. For example, a power model can allow a coal-powered generation plant to rely on water cooling to maintain performance. These continuous integrations are necessary to make SICFMs more realistic (Nan & Sansavini, 2015; Satumtira & Dueñas-Osorio, 2010; Shen, 2013). Thus, synthetic models should be constructed for modular interfacing to maximize portability in interdisciplinary research.

SICFMs may also open possibilities to study interdependencies between technological, social, and ecological infrastructure (e.g., financial, medical, and logistics) for more meaningful results. Infrastructure as technological and physical assets cannot be divorced from their social and environmental contexts, and the interactions between social, ecological, and technological infrastructure have yet to be meaningfully captured (Markolf et al., 2018; McPhearson et al., 2021). Historically, studies that seek to model interactions between civil infrastructure and other domains struggle to include geospatial dimensions or incorporate realistic engineered designs (due to complexity) (Haggag et al., 2020; Min et al., 2007; P. Zhang & Peeta, 2014). SICFMs may provide a realistic foundation that can be coupled with these other domains to extend the results of SICFMs to human capabilities. This extension may reframe priorities for infrastructure based on the impact on people, which has been done in select studies (Oughton et al., 2019;

Thacker et al., 2017; Zorn et al., 2020). But these studies did not delve into social or ecological infrastructure. Yet, they remind us that cascading failure studies should be concerned with human capabilities, not just technological infrastructure systems (Clark et al., 2018). SICFMs may create novel opportunities for this type of advanced research.

Infrastructure managers need greater insight regarding surprise events, and SICFMs might be able to elucidate these insights. Generally, interdependency and cascading failure research use simulations to generate distributions of outcomes, critical failure thresholds, or recovery rates. But, in the state of practice, there was no analysis of outliers or "fat tails" to find low-probability-high-impact vulnerabilities. The concept of *emergence* demonstrates that infrastructures continue to interact in complex ways that have never been imagined (B. Allenby & Chester, 2018; Oughton et al., 2018; Taleb, 2007). Thus, infrastructure managers must meet this increasing complexity with requisite organizational complexity (Boisot & McKelvey, 2011; Chester & Allenby, 2022). Requisite complexity can take the form of more detailed risk analysis to scan horizons for weak signals of change and vulnerability (Chester & Allenby, 2022). Risk analysis for surprise events requires imagination and systematic study of history, especially near-miss events to search for precursor symptoms (Paté-Cornell, 2012). Risk analysis using simple networks (i.e., theoretical) has a limited depth of insight (Hasan & Foliente, 2015; Mahabadi et al., 2021). But synthetic networks' realistic and fine-scale capability may allow for more imaginative and systematic distributions of outcomes for SICFMs (Marcos et al., 2017).

Validation of SICFMs should underpin the modeling process and include many stakeholders. Validation of realistic infrastructure models usually requires real-world data, which is paradoxical because the absence of real-world data is the primary motivator to create synthetic networks. Currently, many studies use publicly available meta-data and comparisons of previous test cases for validation (Ahmad et al., 2020; Birchfield & Overbye, 2020; H. Li et al., 2020; Mohammadi & Saleh, 2021). But the future research community for SICFMs should include stakeholders from outside organizations in the validation process. Stakeholders with engineering knowledge of the imitated networks can give feedback during the modeling process (Ali et al., 2022; Meyur et al., 2020). Also, community stakeholders often possess tacit insight into interdependencies between infrastructure networks and can advise engineers accordingly (Mitsova, 2021; S. Zhou et al., 2020). With this iterative feedback, SICFMs can progressively imitate their real-world counterparts.

Some research possibilities for SICFMs may enhance the use of interdependent models for identifying vulnerabilities, determining maintenance priorities for infrastructure components, and establishing which infrastructure systems are most critical to humanity during emergencies. First, it may become easier to identify the components that may be critical during cascading failure – and thus require maintenance prioritization. Also, realistic interdependency dynamics combined with highly detailed infrastructure can allow for fine-scale sensitivity analysis during the design phase or when performing failure risk analysis (Birchfield & Overbye, 2020). Additionally, because SICFMs should yield more realistic behavior during failure (Marcos et al., 2017), the performance of individual components should be more insightful when including cascades in other critical infrastructure networks (Abdel-Mottaleb & Zhang, 2020). Moreover, realistic behaviors and highly detailed networks can allow social infrastructure and human needs to be considered during failure simulations, linking human capabilities to infrastructure services. Thus, modeling these diverse interdependencies can give a new perspective on infrastructure criticality (Clark et al., 2018).

SICFMs may also improve how the four different types of interdependencies are studied. Physical and geological interdependencies are most commonly studied, whereas logical and cyber interdependencies remain difficult to capture (Cárdenas et al., 2022). Simplistic networks usually only allow for binary (i.e., simple) interdependent relationships between networks (Korkali et al., 2017). But this may change as synthetic networks are designed with more accurate engineering principles. As previously discussed, this capability should allow for realistic connections between infrastructure. In the model, interdependent networks should exchange some resource, energy, or "flow," as Varga et al. (2014) proposed. This type of modeling should allow for a distinct representation of all four interdependency types from Rinaldi et al. (2001).

It is important to also address security concerns for highly detailed models such as SICFMs. If detailed and realistic models for insight into infrastructure systems can be produced with public data and public methodologies, this places a powerful capability in the hands of the public. While infrastructure managers may intend to use them for constructive purposes, some people or organizations may use such models for destructive purposes. Geopolitical strategic competition between adversaries is an essential consideration for critical infrastructure managers and has transformed civil infrastructure systems into military targets (B. R. Allenby, 2016). Infrastructures are also vulnerable to localized or smaller subversive threats such as terrorism (DoD, 2019; Efron et al., 2020;

Grant, 2021; R. A. Miller & Lachow, 2008). Thus, as SICFMs advance, researchers must consider security measures during development and use discretion when syndicating models and results.

Security vulnerabilities for infrastructure highlight an interesting tradeoff associated with SICFMs. There may be a need for insight at fine scales for infrastructure, but how should these insights be protected? Is it better to share these capabilities so many infrastructure planners can analyze their systems for overall robustness? Or would it be better to pursue resilience via other means? The dynamic criticality framework in Chapter 2 highlights critical capabilities for infrastructure organizations that – if mastered – ought to also improve the security infrastructure. Moreover, these types of generalized competencies may not betray the weaknesses of infrastructure systems. On the other hand, SICFMs are a kind of horizon-scanning exercise. Foregoing these types of exercises may cause infrastructure organizations to miss opportunities to bolster specific aspects of resilience for their technological systems.

Another question worth considering is the true utility of developing SICFMs. Indeed, this chapter argues for their insight and necessity. But how much insight toward real-world infrastructure network resilience is actually gained from these types of models? If the right partnerships could be formed, this question would be best answered by side-by-side simulations of SICFMs and cascading failure for real-world network data. But lack of access to real data is what drives the need for SICFMs. So, infrastructure researchers are left with a conundrum: not being able to truly validate their systems without real data, and thus not knowing whether resilience insights from their models are viable or not. Conversely, if validation with real data is required for a synthetic system to be used, this will be an insurmountable barrier for most of these models. Therefore, it may be more reasonable for modelers to seek validation from meta-data, which is often publicly available (H. Li et al., 2020).

If SICFMs should only seek to reach a minimal level of realistic validation, what are the implications of the results from these interdependent cascading failure simulations? What do infrastructure managers and other resilience planners gain from these simulations? It is true that component-specific recommendations will not be possible. However, generalizable conclusions can help inform contingency plans for response to cascading failure. For example, emergency response teams may not know how to plan for the population that may be without power during a heatwave blackout in Phoenix (Clark et al., 2019; Stone et al., 2021; Wittlinger, 2011). While SICFMs would be unable to provide precise locations and populations, a realistic cascading model ought to yield total populations that can inform planning factors. Thus, a strength of SICFMs may be in providing more accurate scenarios to build adaptive capacity for infrastructure organizations (Chester & Allenby, 2022).

Additionally, SICFMs use non-probabilistic design factors such that individual simulations can be analyzed. In contrast, Monte Carlo simulations from probabilistic cascading failure models give generalized results that can only be analyzed via distributions. Although SICFMs have different components than their real counterparts, the results from SICFMs may be used as a horizon-scanning exercise to provide inspiration for the reanalysis of once-ignored real-world components (Chester & Allenby, 2022). This concept ties back to *sensemaking* from Chapter 2. SICFMs should ultimately be considered another means for infrastructure managers to make sense of their systems to build organizational resilience (Hoff et al., 2023).

Lastly, there are some practices that SICFMs should incorporate for more realistic results. First, models that seek to create realistic behaviors must be rooted in realistic demand patterns (Meyur et al., 2020). Power and water infrastructure already have repositories for researchers to retrieve realistic demand patterns for the United States (Frick et al., 2019; Hill et al., 2016; Sharvelle et al., 2017; Thorve et al., 2019; Wilson et al., 2022). Some demand models may even incorporate agent-based behavior, where nodes can have nuanced demands (H. Li et al., 2020; Nan & Sansavini, 2015). Second, models can use time series calculations that synchronize infrastructure network operations (H. Li et al., 2021). Time series will likely be necessary to create the "flows" between networks and may assist in portraying differences in demand (Varga et al., 2014). Third, the condition-based performance of individual components (i.e., reliability) within SICFMs changes the dynamics of cascading failure models. When reliability is incorporated, models typically use time series to introduce condition changes (Bondank et al., 2018; B. Yang et al., 2020; J. Zhou et al., 2022).

The proposed framework is a roadmap for how researchers could use SICFMs to gain a more meaningful and expedited understanding of how infrastructure responds to disturbances. Novel research efforts are immediately needed to confront the destabilizing conditions of the Anthropocene.

3.4 Conclusion

This paper has discussed the intersection of synthetic infrastructure networks, interdependency models, and cascading failure simulations. At the nexus of these domains, there are opportunities for improving how infrastructure managers understand infrastructure vulnerabilities and prepare infrastructure for destabilizing future conditions. The inclusion of synthetic networks will benefit interdependency and cascading failure models. However, synthetic networks still require development, and future work should include the development of synthetic methodologies for other infrastructures besides power and water. Additionally, it may be worthwhile to perform case studies of interdependencies in historical events to aid the development of realistic interdependencies for synthetic infrastructure networks. This real-world data might be used to validate and inform how interdependencies can be integrated into synthetic models. Moreover, future SICFM development should intentionally embed stakeholders for network development, hazard scenario planning for dynamic failures, and interdependent links with continuous flows.

Ultimately, SICFMs seek to create novel insights into interdependent cascading failures. In their basic form, SICFMs are realistic representations of physical assets, relationships, and rules. Synthetic networks are a method to meaningfully organize these attributes. However, if realistic network representations might be obtained via some other means, then the intent of SICFMs will still be satisfied. Naturally, if utility owners share data regarding their networks more frequently, then synthetic networks may become unnecessary. But currently, synthetic networks may be the best available tool for interdependent cascading failure analysis.

Lastly, it is worth recognizing that SICFMs will undoubtedly tend toward computationally large and complex models. However, “There is nothing inherently wrong with complex models, just as there is nothing inherently correct with simple models; it is more a question of appropriateness.” (Logan, 1994) For infrastructure research, simple models are not providing the necessary insights for adequate horizon scanning (Chester & Allenby, 2022). Thus, this chapter suggests that advancing modeling for analysis at fine scales may help infrastructure managers obtain surgical information needed to (Alderson et al., 2022)intervene prior to disasters (Alderson et al., 2022) appropriately. Infrastructure organizations must be prepared to face the accelerating challenges and hazards of the future (Chester et al., 2020). To this end, SICFMs may be rife with insights, and – today – insights are scarce (Chester & Allenby, 2022; Paté-Cornell, 2012).

CHAPTER 4

FUSING SYNTHETIC INFRASTRUCTURE MODELS FOR CASCADING FAILURE ANALYSIS: A PHOENIX CASE STUDY

Chapter 4 appears as a manuscript in preparation for submittal to an academic journal. The anticipated author list is Ryan Hoff, Ryan Sparks, Rui Li, Adam Birchfield, Nasir Ahmad, Nathan Johnson, and Mikhail Chester.

4.1 Introduction

The volatility of the modern world is challenging the operations of infrastructure. Human forces are accelerating at an unprecedented rate producing change across social, ecological, and technological systems (Lewis & Maslin, 2015; Steffen et al., 2015). Aging and obdurate infrastructure and their managers cannot easily adjust and adapt to these changing conditions (i.e., resilience) (B. R. Allenby & Chester, 2018). There are many ways in which infrastructure may fail, but the wicked complexity of these systems often veils which mechanisms deserve scrutiny (Chester & Allenby, 2019a). This complexity exasperates infrastructure managers, who often lack adequate tools to perform risk analysis (Ouyang, 2014; Paté-Cornell, 2012). Unimaginable, extreme, and far-reaching disturbances (i.e., Black Swans) will continue to disrupt infrastructure systems (Alderson et al., 2022). Moreover, limited stakeholder participation, particularly from data owners, can hamper efforts to identify risk and develop contingency plans (Cantelmi et al., 2021). Thus, more advanced tools are needed to scan the horizon for surprises and build resilience for infrastructure systems and organizations without access to proprietary data (Hoff et al., 2023; Marcos et al., 2017).

Researchers have developed many models to improve the resilience of infrastructures. They have sought to model infrastructure interdependencies, showcasing how different technological systems mutually rely on one another and how these behaviors may enhance or reduce resilience (Banerjee et al., 2014; Mahabadi et al., 2021; Ouyang, 2014; Pederson et al., 2006). Other models seek to model how cascading failure can occur within infrastructure systems, frequently including interdependent relationships between multiple networks (Guo et al., 2017; Li et al., 2019; Mahabadi et al., 2021; Valdez et al., 2020). While these models have made significant progress in advancing risk analysis for infrastructure, they usually lack realistic network topology and simulated engineered operations (Mahabadi et al., 2021; Marcos et al., 2017).

To address chronic data gaps, a new model has emerged to provide realistic networks that can be used instead of restricted data. These are known as "synthetic networks" and were initially developed for electrical infrastructure networks (Marcos et al., 2017). These models seek to engineer realistic but fictional models for real geospatial regions. These networks are designed with engineered functions that can be used with simulation packages such as PowerWorld for electrical systems or EPANET for water systems. Thus far, electrical network models have developed a large portfolio of design and validation methodologies for transmission and distribution (Mohammadi & Saleh, 2021). Some work has also been done to develop synthetic network methods for water distribution (Ahmad et al., 2020; Mair et al., 2014; Momeni et al., 2023; Sitzenfrei et al., 2010). However, other infrastructure systems have not received formal attention for synthetic networks (Hoff & Chester, 2023).

Enhanced risk analysis for infrastructure requires more detailed datasets, which may be supplied by synthetic networks (Marcos et al., 2017). Interdependency models and cascading failure simulations often seek to elucidate vulnerabilities. However, without detailed data, these models are often forced to simplify engineering properties and topology, reducing the results' meaning (Mahabadi et al., 2021; Ouyang, 2014). Synthetic networks can, however, serve as foundations for interdependent and cascading failure models. The realistic topology and engineered operations may provide more specific and plausible simulations (Marcos et al., 2017). Results from these networks may be used to research infrastructure network behaviors and combined with social and ecological research scenarios (Hoff & Chester, 2023). With more detailed engineered qualities, simulations that use synthetic models may provide realistic scenarios for extreme events – such as Black Swans. Making sense of this type of risk analysis is the crucial skill infrastructure managers require to build the requisite complexity to face tomorrow's hazards (Ancona et al., 2020; Chester & Allenby, 2022; Hoff et al., 2023).

This study seeks to test the outcome of combining a synthetic power transmission network with a synthetic water distribution network, simulate cascading failures between the two networks, and produce novel insights into the complexities of failure behavior across systems and space. The modeling framework uses the City of Phoenix, Arizona (referred to in this paper as "Phoenix") for model development and testing. Phoenix – with a population of 1.6 million – is the fifth largest city in the U.S. and is subject to extreme summer heat (Stone et al., 2021; US Census Bureau, 2020; Wittlinger, 2011).

This study aims to advance cascading failure models towards improved insight into failure behavior; synthetic models that describe realistic networks are used as the basis (Ahmad et al., 2020; Birchfield et al., 2017, 2019; Hoff & Chester, 2023). Relevant research is discussed in the remainder of the introduction. The methodology explains how the networks are constructed and how cascading failures are simulated. The results contain the outputs from the cascading failure simulation, and the discussion addresses implications for future models and infrastructure risk analysis.

4.1.1 Related Work[1]

Significant progress has been made in cascading failure, interdependencies, and, most recently, synthetic network design (Hoff & Chester, 2023). These advancements now enable the development of more detailed models. Synthetic power and water models have been the most developed methodologies for network generation and will be the focus of this paper. Power networks have had separate research development efforts for transmission and distribution methodologies (Mohammadi & Saleh, 2021). While this study will focus only on transmission, many publications can be referenced for synthetic distribution networks (Ali et al., 2022; Krishnan et al., 2020; H. Li et al., 2020; Mateo et al., 2020; Meyur et al., 2020, 2022; Saha et al., 2019). Synthetic water network models have been developed to simulate water distribution from one or multiple sources to service nodes (Ahmad et al., 2020; Momeni et al., 2023; Sitzenfrei et al., 2010). Synthetic water networks have not received as much focus as power systems. Still, both power and water synthetic methods have been developed and validated to such a degree that they can be used in interdependent cascading failure simulations (Hoff & Chester, 2023).

[1] Section 3.2 contains a detailed literature review of synthetic networks, interdependencies, and cascading failure.

Synthetic transmission network models generally use public data to determine regional electrical demand, and then the network topology is optimized using a variety of economic and design constraints (Birchfield et al., 2017, 2019; Birchfield & Overbye, 2020; Espejo et al., 2019; Gegner et al., 2016; H. Li et al., 2020). Due to the international heterogeneity of transmission systems, studies vary in how they design node topology, but there is agreement that geometric optimization often aligns with the most economical solution (Espejo et al., 2019). In general, it appears that power transmission methodologies are still in a period of rapid development. Methodologies will likely continue to change in the future, as concluded in Chapter 3. Current models are actively used to generate other synthetic datasets, such as annual time series datasets, for use in renewable energy research (Lu et al., 2023). Engineered synthetic models have been used in some rudimentary cascading failure models but have yet to be used in realistic interdependent cascading failure modeling (Mahabadi et al., 2021).

Synthetic water network models follow power models as the next most developed infrastructure system (Hoff & Chester, 2023). There are fewer barriers to developing synthetic water models than power models. Water networks generally follow road topology and have well-understood hydrology design considerations based on a standard use-per-capita (Mair et al., 2014; Sitzenfrei et al., 2010). There are robust estimation models which estimate future demand for all census tracts in the United States, improving modeling efforts' accuracy (Sharvelle et al., 2017). Studies have developed optimization methods, balancing cost and resilience (Momeni et al., 2023). The model used in this study leverages EPANET to engineer the design based on the demand requirements from Sharvelle et al. (2017) and iteratively add booster pumps to maintain the system's pressure(Ahmad et al., 2020). The current state of practice for water models indicates that they – like power systems – are ready to be used for other research efforts such as this one (Hoff & Chester, 2023).

Cascading failure modeling has a variety of methods and applications. A common use for cascading failure models is called dynamic failure: a method that introduces an initial disturbance and then uses a combination of engineered operations and stochastic variables to model reactions (Y. Wu et al., 2021). These models generally require high computation and development time but yield more nuanced results than simplified models (Valdez et al., 2020). These models can be used for various research purposes, such as evaluating the resilience of real-world networks, evaluating different network topologies, identifying critical components, or simulating the dynamics of infrastructure interdependencies (Hoff & Chester, 2023). The last two uses are most relevant to this study, where critical components within the synthetic networks may be identified, and the dynamics via physical dependence will be simulated.

Infrastructure interdependence research analyzes how the systems rely on one another for operation (J. Li et al., 2019). Infrastructure models may seek to simulate four types of relationships, physical (direction operational connections between nodes), geographic (co-location, where state changes in one node would affect another network), cyber (where dataflow between systems is essential to their operation), and logical (dependence by some other means besides the other three) (Rinaldi et al., 2001). Although these four types are known and recognized within the infrastructure research community, it remains difficult to meaningfully capture them via interdependency models. Some relationships are physical, and others are institutional (e.g., governmental, financial) (Hoff & Chester, 2023). Researchers attempt to model these relationships by creating feedback loops between network models. Coding limitations usually demand that relationships can only flow in one direction, which decreases realism. Stochastics are then used to account for assumptions in these relationships (Sharma & Gardoni, 2022).

Interdependence and cascading failure for infrastructure have been ongoing research topics but have yet to incorporate realistic synthetic networks meaningfully. Indeed, the engineered properties of synthetic models may increase realism in simulated interdependencies and cascading failures (Hoff & Chester, 2023). However, thus far, realistic synthetic networks are not yet being used in this capacity. This study uses a real-world landscape to develop synthetic power and water models and explore disturbance-induced behavior for resilience insight and advancement for synthetic networks.

4.1.2 The City of Phoenix

Phoenix can be a realistic example of how cascading infrastructure failures might unfold in an environment experiencing rapid change in multiple domains. The qualitative attributes of the real infrastructure are important when comparing the operational construct of Phoenix to a synthetic model. The discussion must account for these differences when extrapolating the results of a fictional system to the real world. Thus, a brief background of Phoenix sets up the ensuing discussion.

Phoenix is the Arizona State Capital and the county seat of Maricopa County. Phoenix has remained the fastest-growing large city in the United States for a decade, with 1.7 million residents in 2020 (making Phoenix the fifth largest city in the United States). Additionally, there are 4.8 million residents in the combined metro area and county (the fourth largest county in the United States) (U.S. Census BereauBureau, 2020). Despite its reputation as a diamond oasis in the Sonoran Desert, Phoenix does have a history of well-established sustainability challenges (Ross, 2011), many of which may increase vulnerability to cascading failures of infrastructure systems. Development and expansion are not expected to slow down within the metro area in the short-term or long-term future, which will increase the gross demand for energy from the population. Moreover, climate change is expected to cause maximum ambient temperatures to rise (Clark et al., 2019; Wittlinger, 2011), placing environmental performance stress upon the entire system (Allen-Dumas, Binita KC, et al., 2019). Arizona Public Service (APS) and the Salt River Project (SRP) are the two primary power providers in the metro area. APS provides service to most of Phoenix, although it is important to note that the two service providers have interconnected power systems. Also of note is that APS has committed to transitioning all power generation to carbon-emissions-free sources by the year 2050 (APS, 2020).

The Phoenix water supply originates from multiple sources, including the Salt and Verde Rivers, the Colorado river via the Central Arizona Project (CAP) canal, and groundwater. Arizona maintains water reserves supplied by the annual snowfall and precipitation in the northern and eastern regions of Arizona and southern Colorado. These reserves provide long-term water assurance for Phoenix during droughts (Phoenix, n.d.). Three water treatment plants (WTP) treat water from the Salt and Verde rivers, and two WTPs treat water from CAP. Phoenix stores water flows from these sources in large reservoirs and water tanks located to the north in elevated regions, providing the water pressure needed to service all locations in the metro area. In general, the system operates with 100-foot pressure increments. Phoenix also has access to groundwater aquifers, which are occasionally used, but surface water sources are used first (Gober et al., 2010).

Based on known changes expected in the Anthropocene, it is logical to suspect that Phoenix's infrastructure will undergo significant challenges to keep pace. A reasonable hypothetical cascading failure event for Phoenix is abnormal high-power demands caused by extreme heat. In this situation, the distribution network would experience opposing responses in performance capacity and demand, with the performance capacity significantly decreasing (Allen-Dumas, Binita KC, et al., 2019) and the demand from customers significantly increasing (Clark et al., 2019). This inverse shift may represent a critical tipping point, leading to cascading failures that affect services from other infrastructures. This scenario becomes increasingly plausible as the hottest months have become more intense recently, leading to increased heat-related casualties (Hamstead & Coseo, 2019; Iwaniec et al., 2020; Larson et al., 2013) and ever-increasing risk to populations. The power loss alone is a critical hazard to vulnerable populations, but cascading failure from power to water systems in Phoenix could substantially increase risk. Regarding future sustainability, water is among the most important issues for the desert city (Larson et al., 2013; Ross, 2011; Sampson et al., 2016; Z. H. Wang et al., 2019).

4.2 Methodology: Network Creation & Cascading Failure

The overall model was designed as a series of modules that synthesize the power and water networks and simulate cascading failure initiated by transmission line failures (Figure 4.1). Notably, this study incorporates multiple methodologies from different engineering disciplines. Thus, for brevity, the overall methodology is generalized for each module. Detailed explanations of each methodology can be found in the references provided. The synthetic networks use different existing design methodologies and were generated independently. These methodologies will be briefly explained, and the method for the cascading failure simulation will follow.

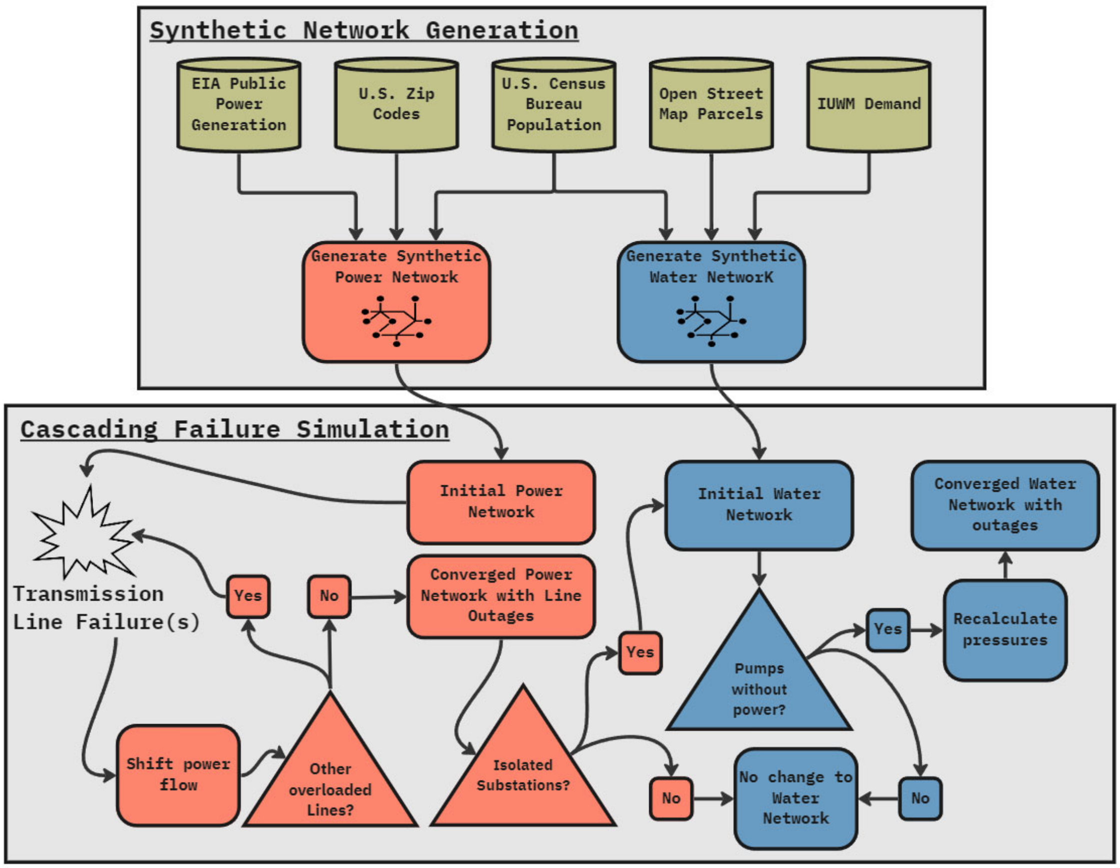

Figure 4.1 – Overall Model Flowchart

Note: The cascading failure is initiated by a transmission line failure. If additional lines are overloaded, the cascading model returns to additional failures until the power flow converges. Dependent outages in the water network will occur if a substation that services a pump becomes isolated.

4.2.1 Module 1: Power Transmission Network (PTN) Creation

The synthetic power transmission network (PTN) is generated using the methodologies from Birchfield et al. (2017) ,and Birchfield & Overbye (2020), referred to as the "Birchfield method" in the remainder of this paper. Appropriately for synthetic networks, the Birchfield method only uses public data to create the network. To determine demand, 2.01 kilowatts (kW) per capita is used as a daily consumption rate (Gegner et al., 2016). The Birchfield method uses census data to generate large demand regions by zip code. These large regions are then divided into smaller, more reasonable regions serviced by individual substations (Gegner et al., 2016). Next, public generating station information is retrieved from Energy Information Administration (EIA), (2022). The closest generators to the area of interest are added first, and more distant generators are added until demand can be met. The Birchfield method then uses Delaunay triangulation to design an efficient graph network of transmission lines iteratively. These iterations also include contingency analysis that tests the sensitivity of different connection possibilities to select the most robust permutations. This network is tested in PowerWorld, a design analysis software application for PTNs. The resulting network for the City of Phoenix resulted in a 3,435 megawatt (MW) total demand, 125 service substations, 11 generators (and associated transmission-only substations), and 302 transmission lines, as shown in Figure 4.2. In this case, generators outside Phoenix were incorporated to provide power balance. Most notably, large solar generation stations and the Palo Verde nuclear generating station are located 45 miles west of the Phoenix area. Despite the distance, they were included in the model to ensure demand provisions were met. Once the synthetic power network was completed, the modeling effort moved to the water distribution network.

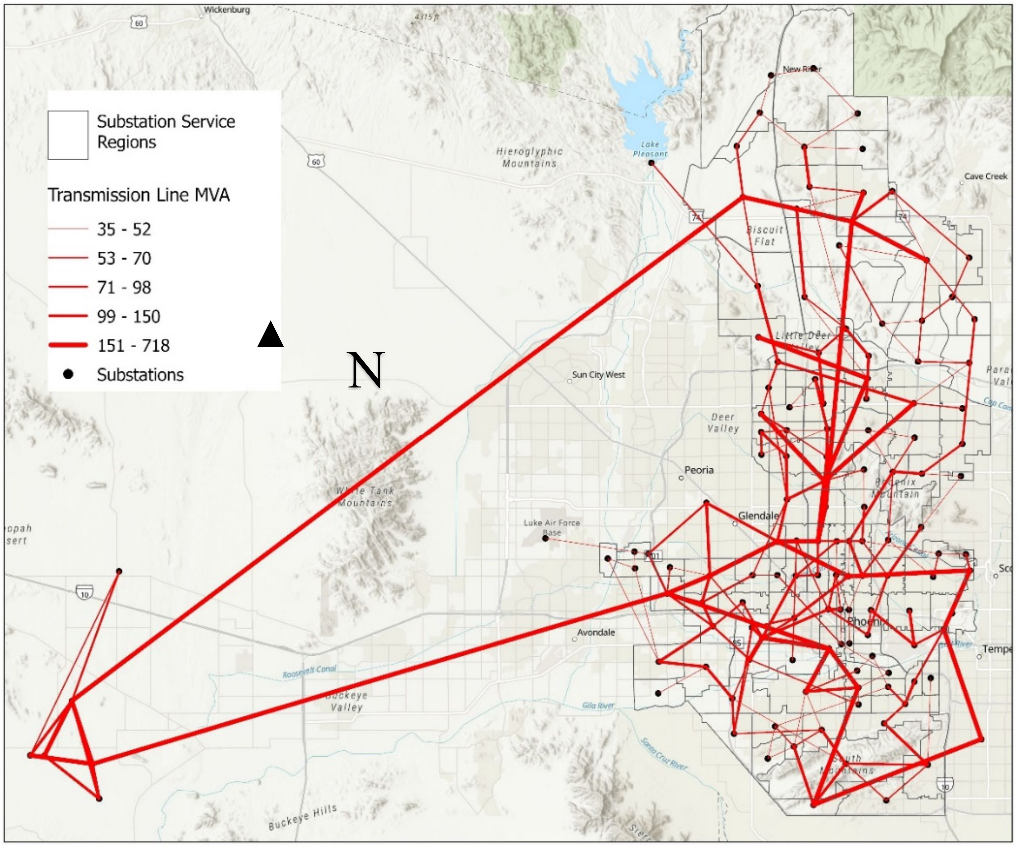

Figure 4.2 – Synthetic Power Transmission Network for Phoenix.

Note: The MVA line weights are divided by quantile.

4.2.2 Module 2: Water Distribution Network (WDN) Creation

The design of the synthetic water network was accomplished by the "SyNF" model created by Ahmad et al. (2020). SyNF is designed to use public data sources and demand models and combine them to generate a pipe network, size pipes for specific water flows, and place pumps to provide pressure. SyNF begins with water demand data for a specific area. The demand data is retrieved from the Integrated Urban Water Management (IUWM) model, which uses census information to approximate specific water demands for the census blocks within the specified area (developed only for the United States and territories) (Sharvelle et al., 2017). Next, SyNF assumes that the water network has the topology of the urban road network (Mair et al., 2014) and thus uses

OpenStreetMap's road network for the given spatial area. For the network's topology, SyNF optimizes the length of the edges in the network using a minimum spanning tree algorithm – creating a main "trunk" line and then adding branched water lines until every node is serviced (Mair et al., 2014). Finally, to provide pressure to the system, SyNF uses iterative tests to find the minimum number of pumps such that 90% of nodes have between 40 and 100 pounds per square inch (psi) water pressure. The resulting WDN for Phoenix has 64,381 edges, 47,115 nodes, and 46 pumps, as shown in Figure 4.3. SyNF creates the WDN as a network file for EPANET, a state-of-the-art application for designing and analyzing water distribution systems. Notably, EPANET uses engineering design principles to simulate water flow through a network, which will be an important facet of the cascading failure simulation.

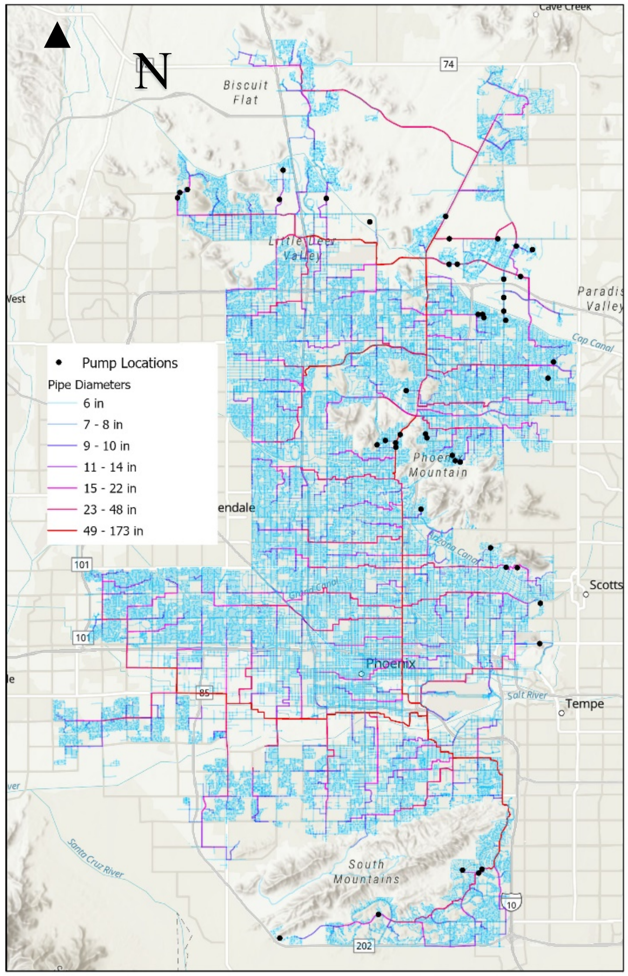

Figure 4.3 – Synthetic Water Network for Phoenix, AZ

4.2.3 Module 3: Power/Water Cascading Failure Simulation

This module joins the two synthetic networks, with water network booster pumps dependent on the substations for power, and simulates cascading failures initiated by transmission lines failures to test how failures may cross over from the power to the water network performance. The cascading failure simulation begins with the power network. This sequence follows the methodology of Sparks et al. (2023). In this case, the synthetic PTN network is loaded into PyPSA, a Python-based model for power flow analysis (T. Brown et al., 2018). PyPSA analyzes the power flow throughout the entire network and reports the performance of components, flagging any violations or overages.

A Monte Carlo simulation forms the basis of the cascading failure model where lines are randomly selected for failure, and the effects of load rebalancing are considered. Without considering any specific hazard, the simulation tests the result of 1, 2, 3, or 4 lines initially failing simultaneously. For each initial failure scenario, three transmission line failure thresholds are tested: 115%, 135%, and 245%, respectively – resulting in 12 different scenarios. The percentages refer to 10-minute, 5-minute, and 1-minute probabilistic overload thresholds for power lines, which are standard time limits often used in decision-making for transmission line protection (Carneiro & Ferrarini, 2011). Ten thousand simulations were run for each of the 12 scenarios, totaling 120,000 unique simulations.

It is also important to note that different actions are taken at these three thresholds. In the real world, automatic load-shedding would occur at the one-minute threshold. There would likely be measured human intervention for ten and five-minute thresholds to smooth out power flows, which may still involve some brown or blackouts. However, the time limit would allow this more nuanced controller intervention (Carneiro & Ferrarini, 2011; NERC, 2022).

The cascading power failure progresses from random initial failures to subsequent line failures and reports any substation failures. When initial line failures are reported, PyPSA attempts to rebalance the transmission system to meet all power demands. If power through the transmission line exceeds the failure threshold, then that line is also considered failed by PyPSA. Also, if all transmission connections to any substation have failed during the cascading failure, those substations are considered failed. When the PyPSA network reaches equilibrium, that simulation is complete.

The cascading failure simulation then assesses the WDN, which depends on the PTN for electricity to booster pumps. The model assumes that power flows from the substations to the booster pumps. When a substation loses power, booster pumps in the same service region as the substation also lose power, causing a drop in water pressure for downstream nodes. This drop in water pressure is simulated for every power loss scenario within EPANET. In every power outage scenario, affected pumps are disabled, and water pressure changes are recorded for every node in the system. The data for these cascading failures are presented in the results.

4.3 Results

The results of the synthetic dependent cascading failure simulation for the individual and combined networks are presented in this section. The power failure simulations are summarized along with visual representations of the failures. Water pressure losses are presented with tables and some mapping examples. Lastly, detailed combined failure scenarios demonstrate the geospatial variance in cascades for different infrastructures.

There were a variety of outcomes when considering the combined cascade between power and water systems. Thirty-one common scenarios accounted for most major power and water outages (Figure 4.4). It is easy to observe that some scenarios only affect small areas of customers from one substation service region. Additionally, water pressure losses are largely contained in or nearby this region. Other scenarios experienced power losses in multiple regions, and water pressure losses extend beyond the power loss areas. These results are explained further in the remaining results section.

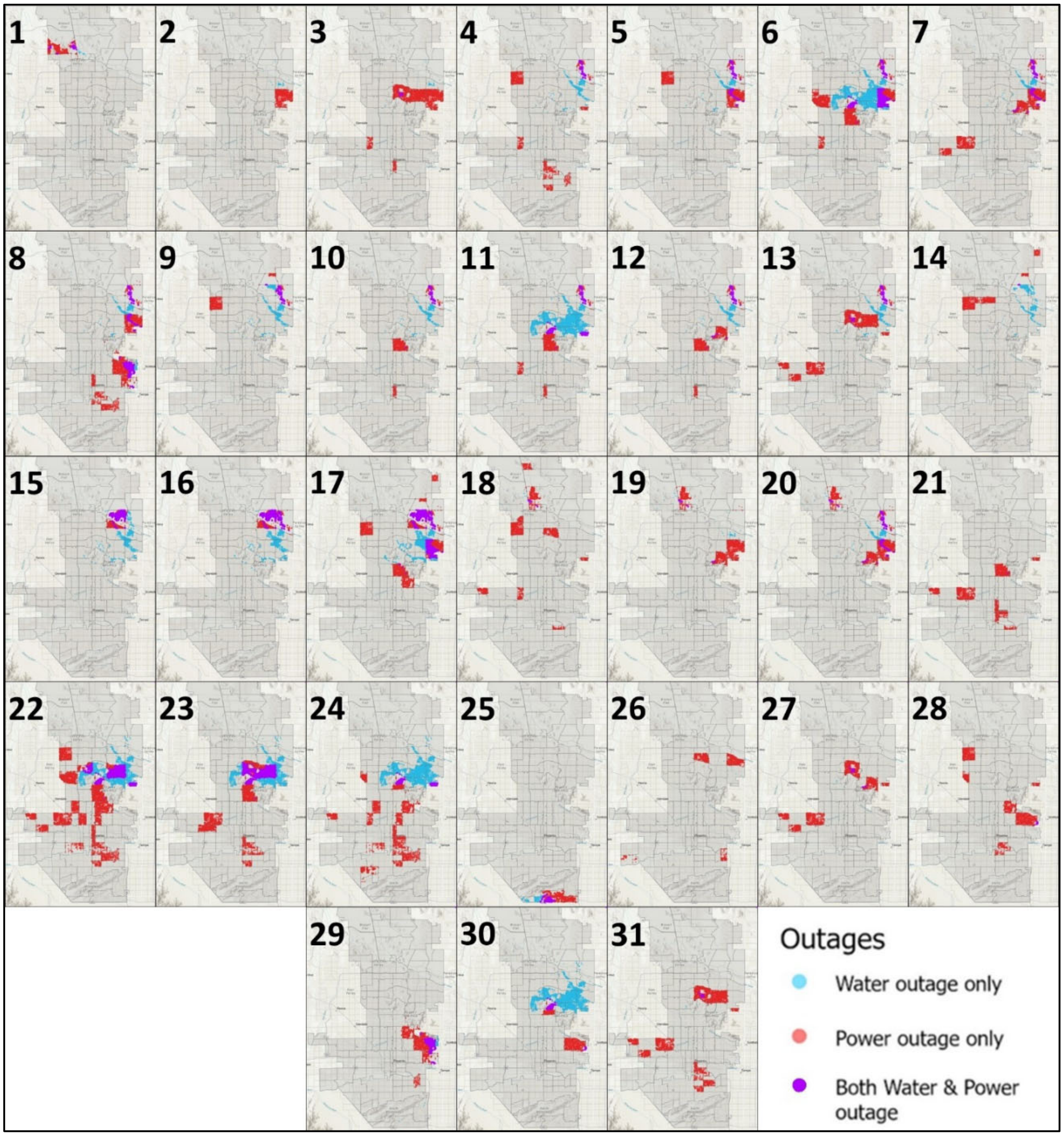

Figure 4.4 – Comparative Water/Power Outage Scenarios.

Note: When referring to scenario numbers, they increase from left to right and top to bottom. (i.e., Row 2, Column 1 is Scenario 8.) See Figure 4.10 for a detailed symbology legend.

4.3.1 Power Failure Results

As expected, the failure threshold and the number of initially failed lines influenced the overall power cascade, as shown in Figure 4.5 and Figure 4.6. The first displays how most initial failures did not precipitate subsequent line failures. Of the

120,000 initial failure simulations, 13,621 (11.4%) cascaded to additional lines. The power system absorbed most line failures and shifted power flow accordingly. Additionally, as the threshold for line failure was increased, the number of cascading line failures decreased. The decrease from 135% to 245% is more notable, where cascades in the system were nearly eliminated. Substation failures also decreased as the failure threshold was raised, as shown in Figure 4.6. This behavior can also be geospatially observed in Figure 4.7, Figure 4.8, and Figure 4.9. There was one substation that had abnormally high failure rates. A generating substation near the Palo Verde generating station failed during all 13,621 cascade events and even failed when there was no cascade (See Table B.1, Substation: "Arlington Valley Energy Facility"). This consistent failure could signal a critical vulnerability in the network.

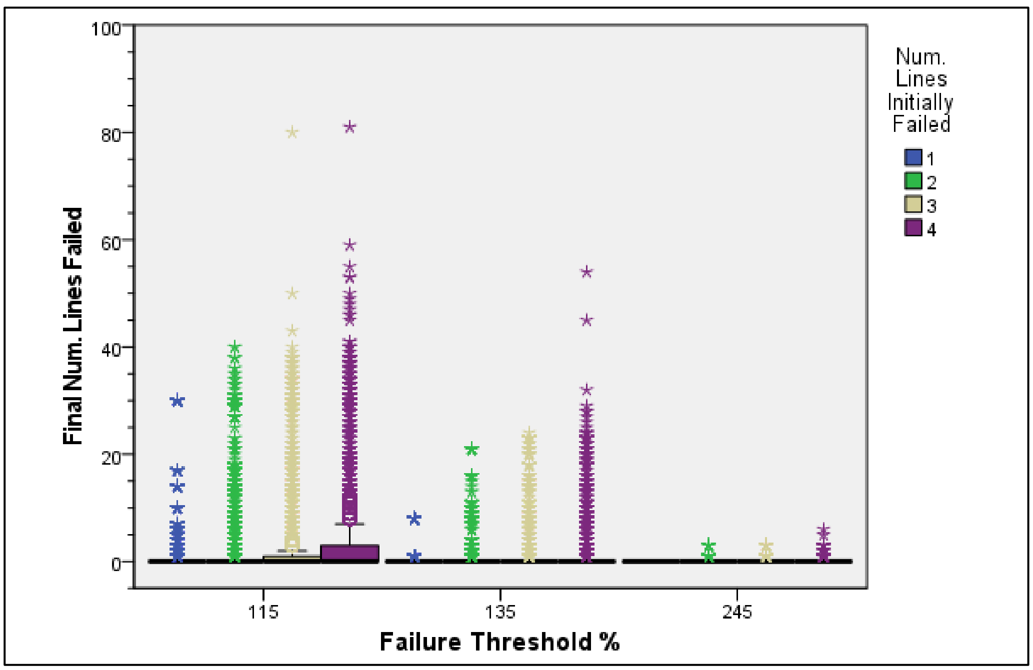

Figure 4.5 – Failure Threshold and Initial/Final Line Failures

There were some outlying high-impact events for line and substation outages. Scenario 22 was the most sensitive outage scenario. During two simulations at the failure threshold of 115%, Scenario 22 had outages spread to 81 lines (4 initial lines failed) and 80 lines (3 initial lines failed). In both cases, the initial failures had three lines in common. In these cases, the initial failure involved a transmission line between two primary generators and the two primary northern transmission lines from the Palo Verde generating station. This initial loss of critical lines led to many more lines overloading. In these two simulations, ten substations and 45 sq-km lost power in one; in the other, nine substations and 46 sq-km lost power.

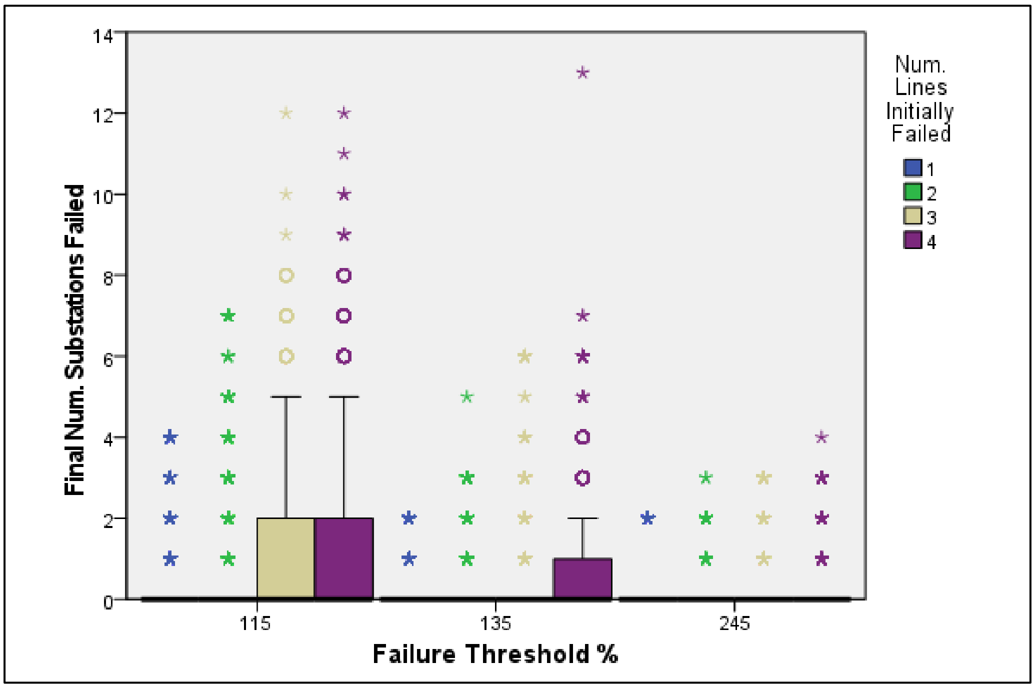

Figure 4.6 – Failure Threshold, Initial Line Failures, and Substation Failures

The geospatial maps of the failures by threshold value showed that some substations and lines are more prone to failure (See Figure 4.7, Figure 4.8, and Figure 4.9). Based on the trend observed in Figure 4.5 and Figure 4.6, It would be expected that, as the failure threshold increased, the failure frequency for all system components would decrease uniformly – which is true for transmission lines. However, some substations seem to be still vulnerable to failure. This trend revealed a small error in how the random selection was applied to the initial line failures, such that substations with only one line connection were consistently islanded during the simulations. This error is discussed further in the *Future Research* portion of the Conclusion. It is also important to note that this pattern occurred primarily in substations with only one transmission line connection. It is well-accepted within cascading failure literature that more connected nodes are more robust, and less connected nodes are more vulnerable (Liu et al., 2019; Valdez et al., 2020). So this behavior also reflects this trait.

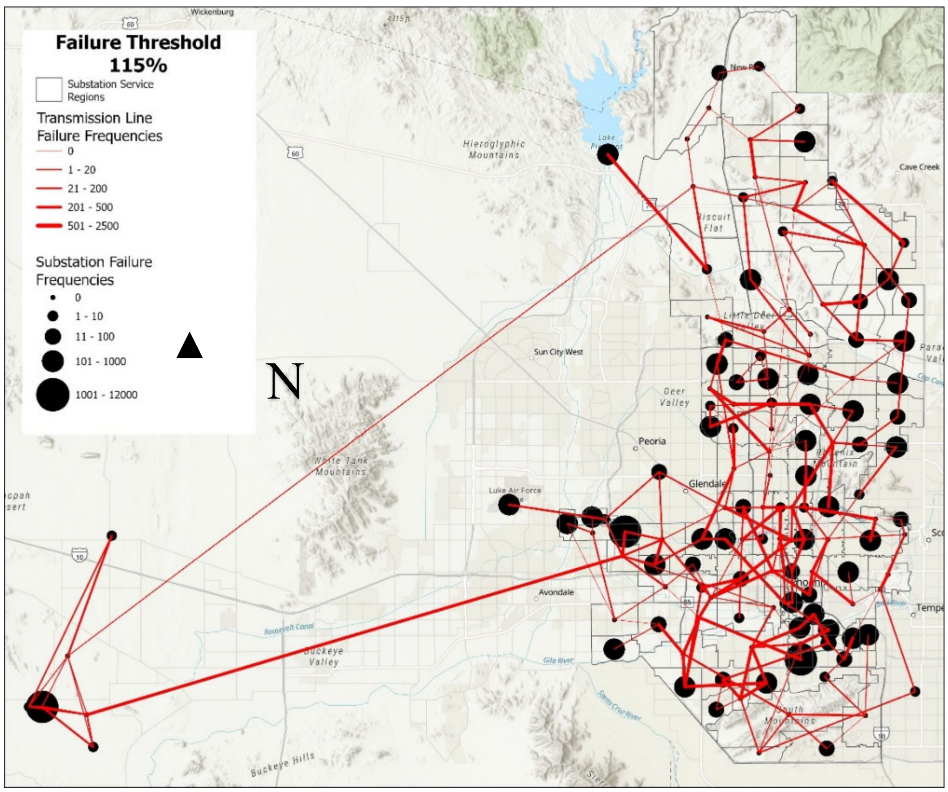

Figure 4.7 – Frequency of Failure for Lines and Substations at 115%-Line Failure Threshold

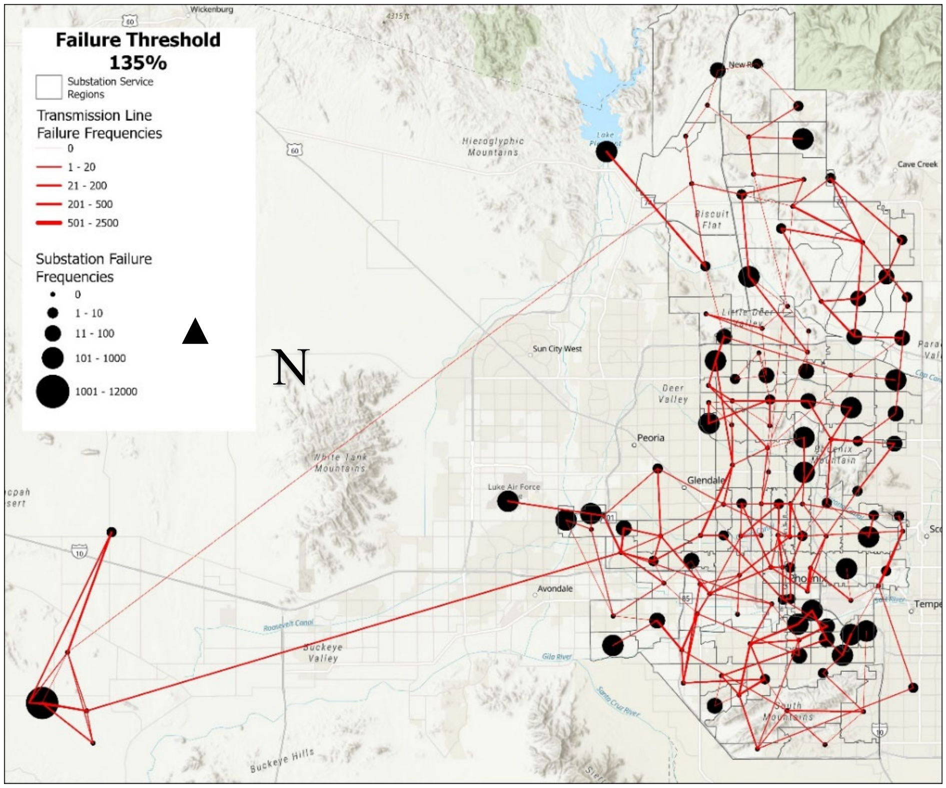

Figure 4.8 – Frequency of Failure For Lines and Substations at 135%-Line Failure Threshold

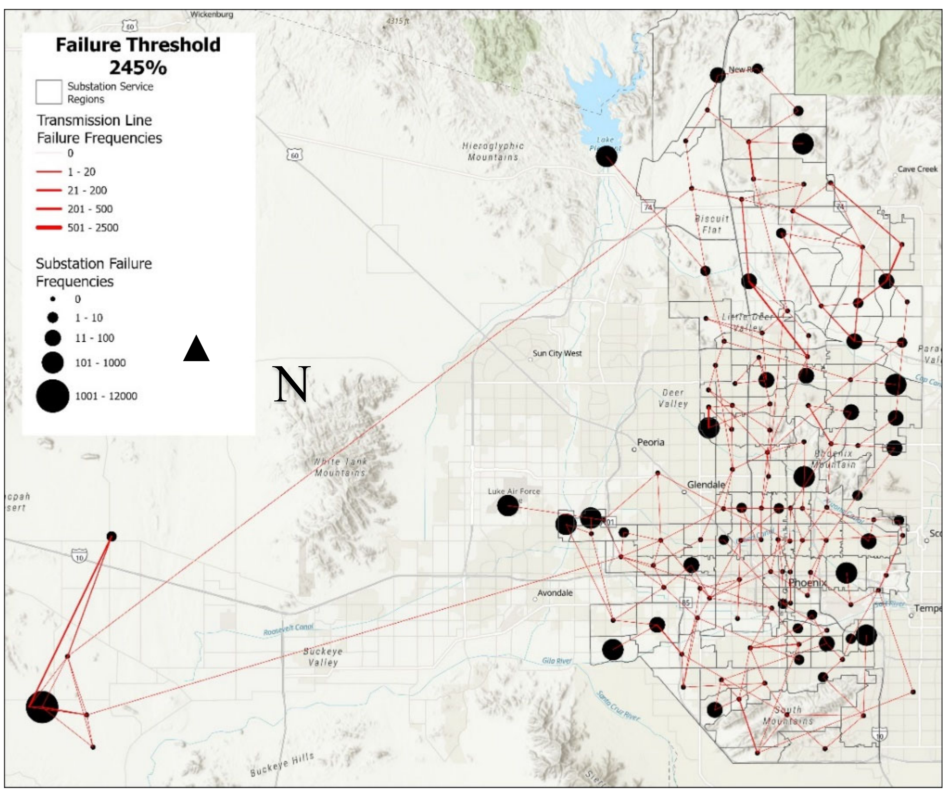

Figure 4.9 – Frequency of Failure for Lines and Substations at 245%-Line Failure Threshold

4.3.2 Cascading Failure to Water Systems

Water "failures" were recorded as pressure loss at the 47,115 water demand nodes. Of the 120,000 power loss simulations, a pump lost power in 4,427 of them. It was discovered that, within these 4,427 simulations, there were 31 pump failure scenarios. Because there were many unique pressure losses across the many water service nodes, binning was used in ten ranges of 10 pounds per square inch (psi) each, from 0 to 100 psi (Table 4.1). The total severity of water pressure loss scenarios is calculated via the sum-product of node count per category and the average pressure value (i.e., for the category, 0 to 10 psi, the nodes are multiplied by 5). The rows are color-coded to reflect the outcome, with red being negative and green being positive. The most severe result was Scenario 17, which had many nodes across all the pressure loss categories. The second and third most severe scenarios, 6 and 11, had the most severe outcomes considering only pressure losses between 10 and 50 psi. These scenarios only occurred two times each out of the 4,427 water failures. However, scenarios 22 and 24 occurred 393 and 623 times, respectively. These two scenarios were the seventh and ninth most severe when considering overall pressure loss in the WDN.

The presentation of these results focuses on pressure drops relative to the baseline pressure of the synthetic WDN; this is because water pressure varies by up to 100 psi between the different nodes. First, there are elevation variations in Phoenix, which can severely affect the pressure in the synthetic network because it is a centralized network where water flow originates from the WTP. Second, the model's creator, Ahmad et al. (2020), notes that only 90% of nodes must be within 40 and 100 psi. Thus, some nodes were below 40 psi or above 100 psi in the baseline network. The pressure drop analysis did not consider nodes initially below 40 psi. Nodes above 100 psi were included because pressure drops at high levels are still meaningful.

Table 4.1 – Water pressure Drop Classes (Count of Nodes)

Scenario	No Loss	0 to 10	10 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80	80 to 90	90 to 100	Relative Severity Rank	Frequency
	Pressure Loss Class Count by Scenario (psi)												
1	45224	1138	526	98	88	32	9	0	0	0	0	28	12
2	43701	3413	1	0	0	0	0	0	0	0	0	29	182
3	7795	39250	53	13	1	2	1	0	0	0	0	20	1
4	2916	43737	252	50	125	35	0	0	0	0	0	19	246
5	2838	43633	408	76	112	46	2	0	0	0	0	14	10
6	30847	9565	1059	1162	1728	1280	1269	179	22	4	0	2	2
7	2993	43388	422	141	123	46	2	0	0	0	0	13	6
8	5327	40550	604	100	145	89	58	77	145	19	1	10	1
9	2416	43697	535	286	101	59	19	2	0	0	0	11	68
10	2916	43703	258	57	142	39	0	0	0	0	0	17	5
11	30872	9553	1051	1264	1600	1300	1270	179	22	4	0	3	3
12	2942	43584	274	123	153	39	0	0	0	0	0	15	1
13	2973	43612	302	64	126	37	1	0	0	0	0	18	3
14	3169	43174	388	296	88	0	0	0	0	0	0	16	39
15	1817	43296	805	327	269	226	127	52	95	78	23	5	77
16	1817	42951	859	524	327	266	126	54	95	79	17	4	1
17	2129	40578	1261	965	1247	465	196	78	95	78	23	1	2
18	40546	6284	266	17	2	0	0	0	0	0	0	26	535
19	39557	7183	294	68	13	0	0	0	0	0	0	25	4
20	3559	42537	688	158	125	46	2	0	0	0	0	12	1
21	47079	2	6	7	17	4	0	0	0	0	0	30	640
22	29973	11206	1248	704	1392	1144	1245	177	22	4	0	7	393
23	29918	11225	1237	769	1341	1138	1263	198	22	4	0	6	4
24	30009	11204	1242	697	1375	1140	1245	177	22	4	0	9	623
25	45435	1211	94	38	50	97	93	91	6	0	0	27	72
26	19159	27956	0	0	0	0	0	0	0	0	0	23	942
27	8734	38223	73	70	12	2	1	0	0	0	0	21	1
28	47099	0	0	0	0	16	0	0	0	0	0	31	356
29	26929	19592	196	24	33	43	56	77	145	19	1	24	1
30	29993	11204	1242	697	1375	1156	1245	177	22	4	0	8	1
31	8721	38325	52	13	1	2	1	0	0	0	0	22	195

4.3.3 Mapping Detailed Cascades Across Infrastructures

The water pressure losses were mapped alongside power loss scenarios to understand better how cascades occur. Scenario 22 was most severe when considering power and water, as shown in Figure 4.10. The figure analyzes line and substation failures for consistent associations with this specific water outage scenario. The results show that many permutations of line failures can lead to the same substation outages. Additionally, many substations may or may not be involved in the cascade. Multiple lines are strongly associated with this scenario, particularly in the southwest of Phoenix. Additionally, the northern transmission lines from the far-western generators consistently failed in the cascade, which may have forced too much power to flow through the southern transmission line and into South Phoenix, tripping a series of lines in South Phoenix. At this point, the power failures cascaded into the city's center, causing the lines into and out of two crucial substations that supplied power to some of the most critical pumps in the city, leading to a large loss of water pressure. The failure of the substations separated from the pressure loss likely plays some significant role in the progression of power losses that cause the pumps in the center to lose power. The level of detail in the results for each scenario gives each one a unique story.

These substation failures precipitate an event that cascades across the entire city. In less severe scenarios, the water system was often able to maintain pressure to most of the system when few pumps were lost. However, in Scenario 22, many adjacent pumps failed, straining those remaining. Consequently, 17,142 nodes (36%) of the WDN experienced some pressure reduction, and 4,357 (9%) of those nodes lost water pressure completely. Thus, the cascading effect on the water system is even greater than those nodes that lose service completely; see Figure 4.11.

Some severe cascades did not include as many nodes but were more severe toward the nodes that did lose pressure. For example, Table 4.2 shows how Scenario 6 only affects 16,268 nodes (35%). However, more than 4,000 nodal pressure losses were between 30 and 100 psi (compared to the 2,000 in Scenario 17). Scenario 6 was caused by a power loss for the key WTP pumps at the center of Phoenix, which effected nodes at lower elevations less but severely affected all nodes higher in elevation.

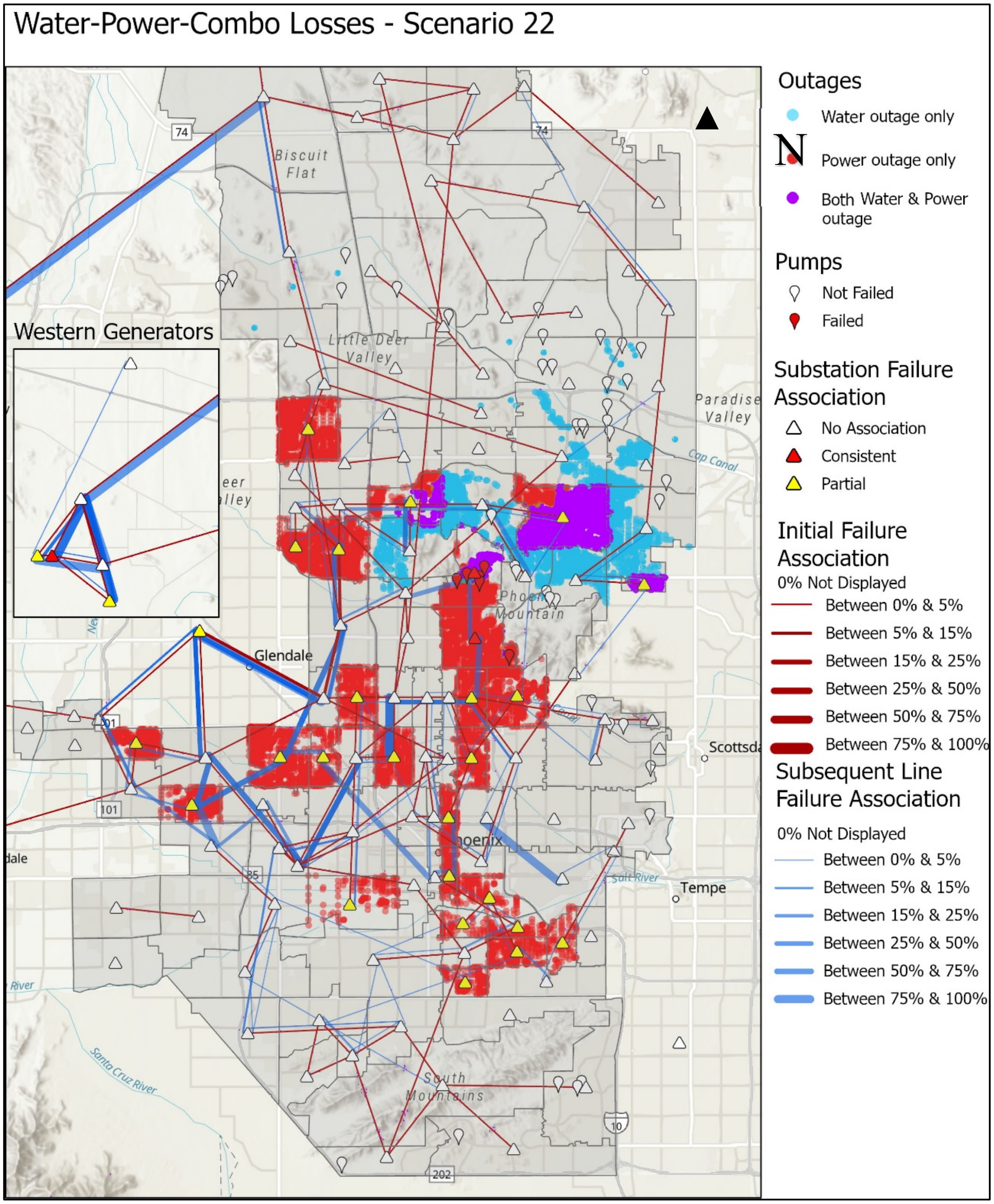

Figure 4.10 – Mapping Cascading Failure Scenario 22

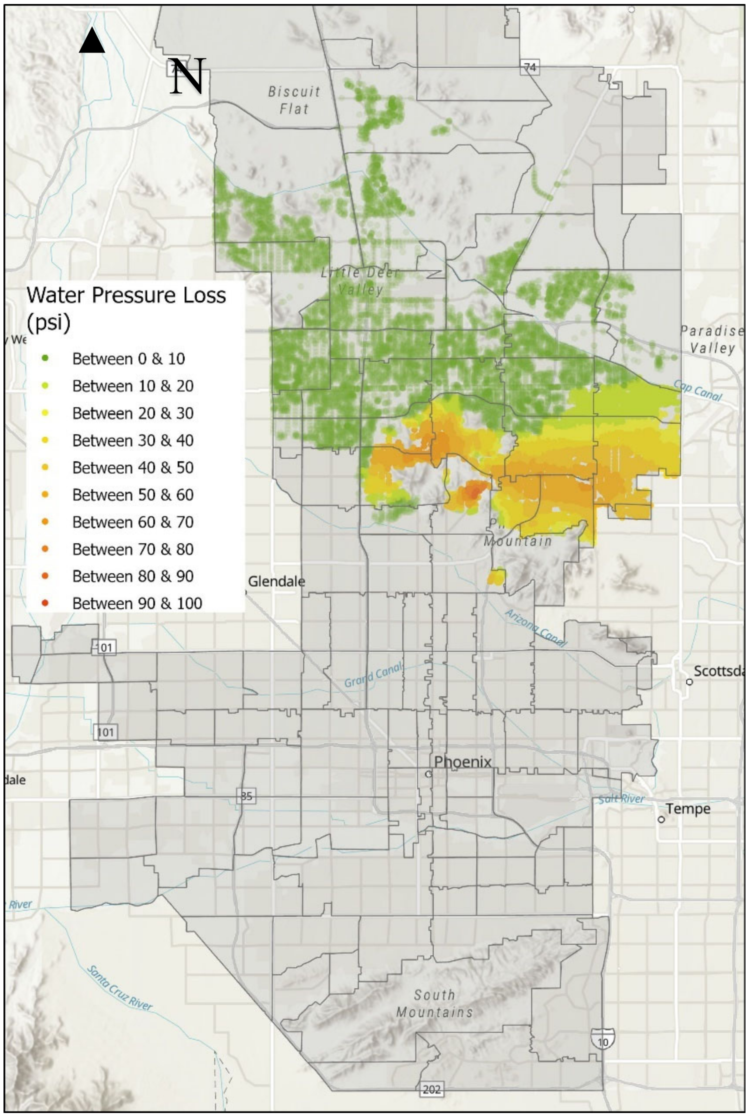

Figure 4.11 – Example of Pressure Losses for Nodes in Scenario 22

Note: Not all nodes have completely lost water service, but this figure demonstrates that cascading effects may be more far-reaching than simply at those nodes that drop below 40 psi.

The overall cascades can be analyzed more simply to demonstrate the severity of the various scenarios – instead of analyzing probabilities of outages for lines and substations or specific pressure losses for each node. In this case, the 31 cascade scenarios can be reduced to simply power loss areas, water loss areas, and areas where the two outages overlap, as shown in Table 4.2. Water outages were identified at nodes above 40 psi in the initial network and fell below 40 psi after a water outage occurred. In some cases, large power outages can occur with minimal water service losses (i.e., Scenario 3). Conversely, there can be large water outages with smaller power outages (i.e., Scenario 30). Power and water failures may be geographically separated or overlapped. Scenario 22 is the most severe scenario when considering both power and water losses, demonstrated by Table 4.2. In this case, power losses occurred across a large area of South and Central Phoenix, with water pressure dropping below 40 psi across much of the city center. Other severe Scenarios, like Scenario 24, had nearly the same number of nodes that lost only Power or only Water, and there were very few nodes that lost both services. This location difference highlights the disparity between geographic and physical interdependencies. Physical interdependencies can involve geographically disparate failures(Rinaldi et al., 2001). Scenarios 6 and 17, while severe, only occurred twice each. However, scenarios 22 and 24 occurred more frequently (392 and 623). This higher rate of occurrence could signal specific vulnerabilities within the associated components.

Table 4.2 – Service Node Counts in Power/Power Cascade Scenarios

Cascade Scenario	*No Outages*	*No Water*	*No Power*	*Both*
1	46280	28	758	49
2	45912	49	1154	0
3	43089	47	3921	58
4	44573	579	1881	82
5	44459	416	2021	219
6	39235	3674	3341	865
7	43375	398	3104	238
8	42663	521	3348	583
9	45081	849	1074	111
10	45243	579	1207	86
11	40837	4177	1739	362
12	44553	555	1901	106
13	42385	568	4015	147
14	44807	708	1598	2
15	44992	981	551	591
16	44619	1124	647	725
17	40435	1545	3744	1391
18	44036	14	3055	10
19	44507	64	2528	16
20	43930	411	2526	248
21	44337	0	2774	4
22	34554	2867	8204	1490
23	38721	2511	4010	1873
24	38545	4081	4217	272
25	45746	242	983	144
26	45478	5	1620	12
27	43720	5	3322	68
28	44048	1	3052	14
29	44585	105	2061	364
30	41368	4176	1379	192
31	42377	5	4675	58

4.4 Discussion

These simulations demonstrate plausible outage scenarios in realistic power and water networks, providing resources to analyze interdependent cascading failure, envision potential Black Swan scenarios, and unlock potential analysis for other research fields. Interpretations from these and similar results from future models may aid in identifying vulnerabilities, quantifying risks, and envisioning future scenarios for social, ecological, and technological systems. These possibilities, as well as future research opportunities, are discussed in this section.

4.4.1 Interpretations of the Results and Comparison to Phoenix Real Networks

Before providing recommendations, this simulation's results should be contextualized and compared with real-world factors. As intended, the power and water networks attempted to continue providing service when disturbances occurred. In 89% of 120,000 simulations, the networks provided service to all nodes without interruption – despite initial transmission line failures. Moreover, when service outages did occur, the effects were usually minimal. This robustness is expected and desirable in realistic networks. Thus, the synthetic networks fulfilled expectations in that respect. When analyzing specific portions of each system, there were some consistent vulnerabilities. An outlying generator substation consistently failed in the power network for unknown reasons – a potentially critical vulnerability. For the water network, there were pumps clustered near the northern water treatment plant that, when they failed, caused large pressure losses in some scenarios. These observations reveal areas for continued improvement in the model. Additionally, because access to real-network data for Phoenix was not possible to validate the synthetic models, public data was used as a comparison to contextualize how the outputs might be considered in the greater context of infrastructure resilience. This section discusses these comparisons for the power and water networks and their dependent relationship.

The power network provided sufficient variance and robustness when met with disturbances. When the Monte Carlo simulation presented the most disadvantageous scenario (115% failure threshold with four initial transmission line failures), the network did not fully collapse and, in most cases, continued providing power to most of the network. This study did not push the network to total collapse with progressively more transmission line failures because the progressive failure threshold was not an objective. Progressive failures are more commonly observed in percolation theory studies (Mahabadi et al., 2021). Rather this study sought to create dynamic failures driven by engineered operations – not stochastics. Transmission line failures were used as the initiating disturbance due to the high association with their failure and blackout events (FERC & NERC, 2012; NERC, 2004). As expected from past network resilience research, highly connected substations failed less often, and those with fewer connections failed more often. The robustness and realistic power dynamics imply that synthetic power networks may serve as suitable platforms for future cascading failure research.

When evaluating the power network's realism, it was not possible to compare it with the real transmission network for the city of Phoenix or substations and their service areas. Instead of real data, outage distributions from this simulation were compared with data from the energy information administration (EIA) for major U.S. power outages in 2020, as shown in Table 4.3 and Figure 4.12. The major U.S. outages' mean, median, standard deviations, maximum, and percentiles were consistently one order of magnitude higher than the synthetic outage results. The distributions display similar behavior, with the synthetic power failures centering near 10,000 people and the EIA data centering around 100,000 customers. The EIA data focused primarily on the most significant outages in the United States, frequently involving metro areas with multiple cities and sometimes regional cascades. In contrast, this study focuses only on the City of Phoenix and does not consider the Phoenix metro area, which is more than triple the population being considered. This size difference naturally limits the cascade size in the model. However, the similarity in distribution and patterns of descriptive statistics suggests that the outages of the synthetic power model using Sparks et al. (2023) methodology are within an acceptable range for a city this size.

Table 4.3 – Cascading Power Outage Validation

		Population Affected (U.S. Data)	*Population Affected (Synthetic)*
N		157	16,808
Mean		161,108	15,859
Std. Deviation		241,800	16,661
Minimum		1	353
Maximum		1,400,000	144,051
Percentiles	25	52,082	4,754
	50	78,314	9,049
	75	156,750	22,610

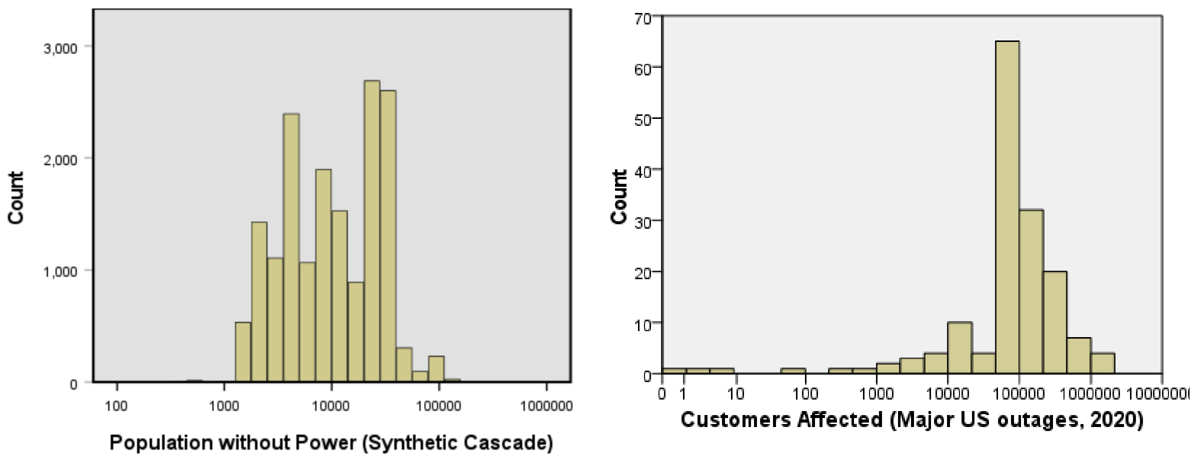

Figure 4.12 – Cascading Power Outage Distribution Validation

The synthetic network was compared to public information for transmission networks in the United States. Some basic public data is stored on the Homeland Infrastructure Foundation Level Data (HIFLD) database, which contains generalized data for the national power network in the United States. Data accuracy and completeness vary depending on location, but – in place of real network data – it was helpful to compare topologies for general similarities and differences (see Figure 4.13). Some of the major features of the synthetic network match the HIFLD network. Both networks have a northern and southern connection flowing into Phoenix from the far-west generators (i.e., Palo Verde generating station). Additionally, those same western generators appear to be an important part of the system in the HIFLD dataset, which is consistent with the design of the synthetic network. Also, for both networks, the density of substations in Central/South Phoenix is higher than in Northern Phoenix. Two notable differences are in the far-south and far-north regions. The HIFLD network does not have substations in some of these low-population areas, and the synthetic network has substations in those locations (although, in the synthetic network, these were the lowest power demand regions in the city). For future research, manual adjustments for topographical features and population should occur while calculating substation service regions and network topology.

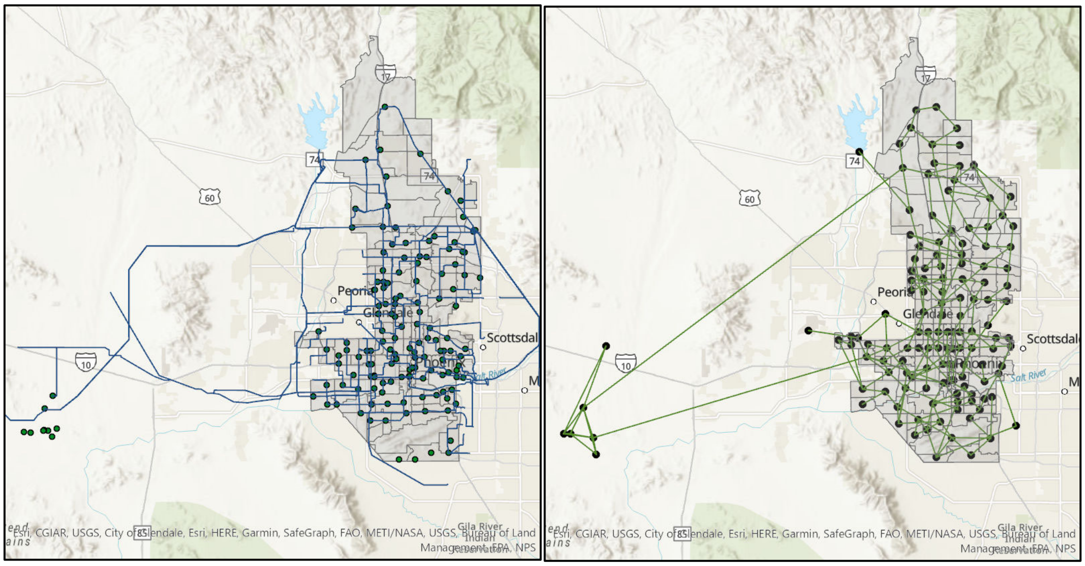

Figure 4.13 – Comparison of Phoenix HIFLD Data (Left) and Synthetic Network (Right)

Note: The HIFLD database is known to be incomplete. Thus, it serves only as an informal comparison resource for the synthetic power network.

The water network exhibited realistic behavior in response to pump outages, despite some inaccuracies regarding components in the network construct. Pressure losses were graduated across regions and demonstrated significant variability across the 31 scenarios where pumps lost power. The system displayed resistance to total failure, even when large outages occurred. The largest water outages typically occurred when the cluster of pumps near the WTP lost power. However, scenario 17 was one exception. Although it did not have as many high-pressure drop nodes as scenario 6, it had the largest city-wide pressure drop of all scenarios. Notably, this outage occurred without the WTP pumps losing pressure. Rather, it occurred because pumps in central and south Phoenix lost power, drawing flow away from northern (i.e., higher elevation) nodes, which had simultaneously experienced some pump losses. However, is scenario 17 realistic? Contextualization and comparison with real-network data are required, and there are some inherent differences to discuss.

For security purposes, employees at the Phoenix public works department could not provide the specific layout of the water system. However, they provided a generalized interview description(Kelso, 2022). They provided qualitative information and a summary table of pipe lengths and diameters across the city. Qualitatively, there are notable differences between the real and synthetic WDSs. The real WDS provides power backup generators for the water distribution plants and larger (but not all) pumps across Phoenix. Therefore, in an outage, there is a grace period to restore power before pumps fail. Additionally, rather than supplying direct pressure to the system, water tanks in high locations are often used to service nodes in North and South Phoenix hilly regions, allowing for local clusters in the WDN and providing additional redundancy. Tanks have a reserve supply if no power is available, and backup generators can also allow for maintaining water tank levels for a graceful period. The synthetic WDN system does not contain water tanks or pump backup generators. Thus, city-wide pressure losses in this model, such as scenario 17, would likely be conditional upon long power outages that exhaust water tanks and backup generator capacity.

Regarding pump design, the synthetic system had a loose-fit similarity to the available data for phoenix pumps. The Phoenix WDS maintains an inventory of 105 pumps across the city. Smaller pumps provide as little as 40,000 gallons per day (GPD), while larger pumps or pump clusters provide 160 million gallons per day (MGD). The synthetic system created 46 pumps across the city to maintain pressure. The smallest pump provided 230,000 GPD, and the largest provided 80 MGD. Although this is not as large of a range as the real network, with fewer pumps, it is notable that the minimum pump size provides much higher volumes. So the average flow from each pump may be larger than the real Phoenix network. Moreover, real Phoenix pumps are often co-located, servicing the same parcel regions for redundancy. The synthetic applies only one pump node per location, regardless of flow requirements. These qualitative differences may still be realistic because only generalized comparisons should be made for real WDN pump infrastructure.

The pipe sizes and lengths for the synthetic and real WDNs were within the same order of magnitude in most pipe sizes. The largest difference in pipe length was for 11-to-16-inch distribution and 25-to-60-inch main pipes, as shown in

Table 4.4. Additionally, the synthetic system had six times more pipes over 100 inches than the phoenix system. The construct of the synthetic system likely accounts for this difference. The synthetic system uses a minimum spanning tree method to design one unified network. Thus, the largest pipe sizes will transport large volumes of water, whereas real systems may divide this transport between multiple main water lines. Additionally, the synthetic model may have fewer miles of pipes because the system was designed as one network rather than the ad hoc sprawl design that developing cities tend to have from growth and development.

Table 4.4 – Water Pipe Size Comparison

Bin sizes (in)	*Synthetic Total Length (ft)*	*Synthetic Total length (mi)*	*Actual Total Length (ft)*	*Actual Total Length (mi)*
≤ 10	25,879,552	4,901.4	28,849,404	5,464
11 to 16	685,833	129.9	5,617,677	1,064
17 to 24	510,822	96.8	782,404	148
25 to 60	687,090	130.1	1,512,625	286
61 to 100	116,094	22.0	249,015	47
101 to 173	62,811	11.9	10,206	2
TOTAL	27,942,171	5,292	37,021,331	7,012

4.4.2 Large-Scale Outcomes and Black Swans

A primary goal of this study was to observe if the cascading failure between the power and water networks would yield outcomes that could be classified as Black Swan events. Referring back to the introduction of the term in Chapter 1, black swans must carry a large impact (positive *or* negative). Moreover, the impacts are not only physical but reverberate through all of society in various ways. Black swans present challenges to infrastructure managers in two ways: likelihood (very low) and perceivability (very low) (Paté-Cornell, 2012; Spiegelhalter & Riesch, 2011). As to the likelihood, infrastructure managers do not have the time, resources, or human resources to prepare their systems for every low-likelihood scenario – even the most extreme scenarios. However, regarding perceivability, infrastructure managers rarely perform robust enough risk analysis to elucidate black swan scenarios. Factors of safety area are commonly used in the design, but they are often static, and the Anthropocene, notably extreme weather events, will continue to exceed these standards (Allenby & Chester, 2018; Markolf et al., 2021). Thus, Paté-Cornell (2012) posits that more nuanced modeling efforts can provide unique insights, balancing model complexity and generalization (recognizing that oversimplification in modeling causes extreme events to be overlooked, leading to calamities when extreme events arrive).

When considering infrastructure failures, it is also important to distinguish between black swans and another term called the "perfect storm." A perfect storm is an alignment of many unlikely but known events that cause a much more extreme outcome than expected (Paté-Cornell, 2012). Hurricane Katrina in 2005 is an example of a perfect storm. The scenario involved a severe storm with extreme rainfall, cross-organizational communication failures, slowness of response, and historical infrastructure mismanagement (Leavitt & Kiefer, 2006). All these events were understood and foreseen, disqualifying Katrina as a black swan. Large-scale power outages, such as the northeast blackout of 2003, are also perfect storms because large-scale power outages have been a known possibility for many years. However, the scale of complexity for interconnected infrastructure systems creates the possibility for innumerable combinations of negative outcomes (Arbesman, 2016; Chester & Allenby, 2019a). For example, a large power loss occurred in Arizona/Southern California on September 8th, 2011. The initial power outage was a perfect storm of under generation, peak demand in San Diego, and the failure of a single critical transmission line in Southern Arizona. When the transmission line failed, San Diego's power demands were automatically rerouted through lower-voltage systems, overloading them to the point of failure. The power failure cascaded to other infrastructure networks in San Diego, causing traffic gridlocks in San Diego, aviation delays, water service failures, and sewage system failures (including sewage spills on the beach and in the ocean) (FERC & NERC, 2012). The initiating event was a power outage (i.e., a known event). Still, the effect of that single event had surprising and expanding effects on other infrastructures and the society of San Diego. This expansion of cascading effects is an excellent example of how interconnection between infrastructure networks greatly reduces the ability to perceive how known failures can cascade into unknown domains. Often, infrastructure managers cannot anticipate how a known accident can spread to cause a surprise catastrophe. These mysteries and widespread effects capture the essence of a black swan.

Therefore, while there were extreme scenarios in this modeling effort, they cannot all be classified as Black Swans. In the two most extreme power loss cases, 80 and 81 lines failed. However, these scenarios initially involved two of the most critical lines from the Palo Verde generating station to Phoenix. Logically, their loss should cause a large outage, and events like this would be perceived and planned for by electrical engineers. However, in the case of Scenario 22, with both a severe power and water outage, there were 26 possible associated transmission lines – only two of which were major transmission lines from generating substations. These lines may not have been given as much security scrutiny or contingency planning as other major lines. Moreover, the wide range of line associations with this scenario creates many more ways the Scenario 22 power loss can cause a large water service loss (See Figure 4.10). This deep uncertainty hints at Black Swans.

Another example is Scenario 17, where 95% of the WDN experienced a pressure drop. While this does not mean that 95% of nodes lost pressure, this combination of power and pump failures had effects far outside the original failure zone. Over 40,000 nodes experienced a small pressure drop (0 to 10 psi). For most nodes, this would probably not be very important. However, for nodes near the acceptable service of 40 psi, this would drop them below – which happened to 2,396 nodes in Scenario 17. As previously discussed, it would require many unlikely events to create such a large pressure drop; thus, this scenario may not be worth consideration. But frequently dismissing unlikely outcomes during risk analysis leaves societies unprepared for the surprise of extreme events (Paté-Cornell, 2012).

4.4.3 Synthetic Network Use for Urban Resilience and Sustainability Scenarios

Suppose infrastructure managers wish to ferret out scenarios for black swans in infrastructure and how the cascading effects might cascade to other parts of society. In that case, a change in risk analysis is needed. First, models cannot over-rely stochastics. They must include prior knowledge and inclusion of the system fundamentals (Paté-Cornell, 2012). These two principles highlight how infrastructure organizations must be able to pivot resources in dynamic environments by remembering past events (i.e., what has worked and what has not) and unlocking innovation within the organization (Hoff et al., 2023). To this end, this study creates realistic networks via engineered models instead of using aleatory or theoretical principles. These networks and simulations can open up opportunities to provide engineered resilience analysis for future scenario research. For example, Iwaniec et al. (2020) modeled future scenarios for the Phoenix metro region, projecting future urban growth and agricultural changes and incorporating climate adaptation. Coupling such scenarios with a model like this study could expand possibilities, investigating how power demands, climate change, and water availability might interact with synthetic infrastructure models for the same region. The results may provide insight into the challenges for infrastructure networks facing rapid urbanization and climate change in a desert city.

Additionally, scenarios can be advanced further with consideration of the social implications of power outages as maximum ambient air temperatures are expected to increase, which decreases the efficiency and performance of power systems and poses an increased threat to vulnerable populations (Allen-Dumas, Binita, et al., 2019; Andresen et al., 2023; Hamstead & Coseo, 2019). For example, an overlay of demographic populations with Scenario 22 may provide insights into how vulnerable populations could experience power and water loss. While specific locations of outages cannot be extrapolated from the synthetic network results, realistic behavior could help emergency planners estimate affected populations in the event of large-scale power outages combined with climate-change-induced extreme heatwaves that Phoenix may experience (Clark et al., 2019; Stone et al., 2021). As another example, cascading failure analysis, as used in this study, could be paired with scenarios for electric vehicle adoption in a region – which is currently a question in the state of California. Researchers may seek to know if the additional load can be absorbed by the power transmission and generation system and if there will be any interdependent cascading effects on the water systems or other infrastructures. To study a question like this, other modeling considerations would be necessary due to potential voltage complications (Arfeen et al., 2020; Meyur et al., 2022; Muratori et al., 2021). These types of studies may help infrastructure managers analyze extreme events within networked and coupled infrastructure systems as an exercise to either prepare for surprise or scan the horizon for where resilience-building efforts may be the most effective in meeting future complexity (Alderson et al., 2022; Chester & Allenby, 2022).

This type of scenario insight highlights how SICFMs may be an important resilience tool for continuity of operations (COOP). Government and non-governmental organizations are responsible for developing plans to sustain operations and services at all levels (FEMA, 2011). This capability is considered a critical national infrastructure when viewed as a collected capability among governmental and non-governmental organizations (Moteff, 2015). Interdependency modeling is considered a critical research area to improve plans for COOPs from a national defense perspective (Pederson et al., 2006; U.S. Army, 2015). Additionally, COOPs for infrastructure systems also directly affect COOPs for other organizations that provide essential services. Thus, these SICFM simulations may provide crucial sensemaking exercises for many stakeholders besides infrastructure managers.

The need to use SICFMs to improve contingency plans such as COOPs also highlights another concern regarding SICFMs and their connection to infrastructure systems as strategic security assets. The gap between infrastructure's significance to military and civilian operations continues to shrink. International conflict occurs daily via the internet (B. R. Allenby, 2016; Jakubowski, 2019). Infrastructure systems that were once independent are now coupled with one another in wickedly complex ways (Chester & Allenby, 2019a). Thus, SICFMs may provide additional tools for malignant actors to analyze infrastructure systems for vulnerabilities. But it is likely that these capabilities to analyze and act on vulnerabilities are already being developed. This should simultaneously be alarming for infrastructure managers and also compelling to develop the same capabilities to counter the vulnerabilities before they are exploited (Chester & Allenby, 2020). Indeed, as this gap diminishes between civil and military operations for infrastructure, stakeholders should consider how SICFMs like this study could both assist and harm their systems as well as other dependent systems.

4.4.4 Future Research

Industrial validation from the utility provider on the synthetic electrical network would provide helpful feedback. Ali et al. (2022) successfully used industrial validation and provided iterations of the synthetic network to the utility owner for evaluation and refining the design from feedback without the real network data being released.

The results showed several substations with identical initial-failure frequencies, regardless of line failure threshold. This repetition should not have happened if line failure selection had been random. When analyzing the results, it was realized that the random seed supplied for initial failure selection was tied to the iteration number, which led to a consistent pattern in the random selection across the 12 rounds of 10,000 simulations. Fortunately, this did not cause all substations to follow a consistent pattern of behavior – only a small selection. These substations had only one transmission line connection, such as with substation "Phoenix_12," as shown in Figure 4.14. Because there was some consistency in how the lines were randomly selected for failure, this caused "Phoenix_12" to fail 0, 2, 53, and 80 times for 1, 2, 3, and 4 initial line failures, respectively – regardless of line failure threshold. This issue will need to be corrected in future versions of the cascading failure model to improve the Monte Carlo simulation.

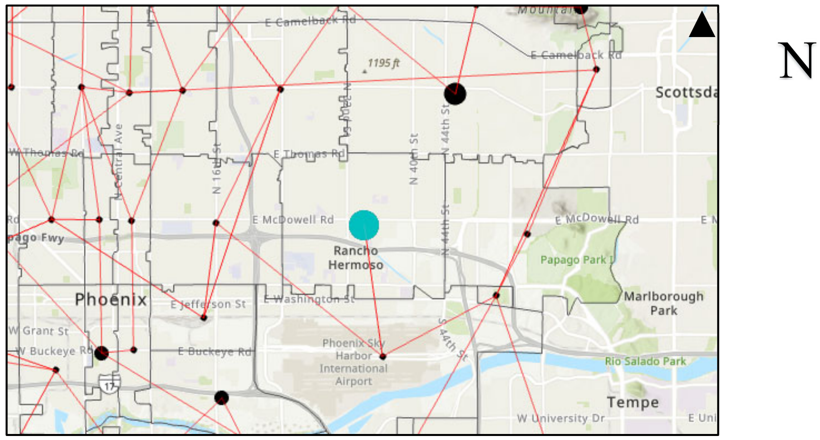

Figure 4.14 – Substation "Phoenix_12" With Only One Line Connection

Additionally, several changes could be made to the synthetic water model for a more realistic water network. The system relies completely on booster pumps to provide pressure to the system. Real networks indeed use booster pumps. But they do not use them exclusively. Most water distribution networks also leverage gravity with water tanks and towers, which are not present in Ahmad et al. (2020).

Moreover, backup generators could also be added to WDN pumps as stochastics to increase realism. Additionally, the network topology could be modified to ensure a looped design. The current model uses a minimum spanning tree model. Although it does satisfy pressure, velocity, and flow design parameters for most of the pipes and nodes, a looped methodology may yield more realistic behavior. A comparison study between the two topology methodologies may aid in refining the realism of the water network design. Or perhaps comparing the results of multiple synthetic water model methodologies may provide insights for improvement or accuracy.

4.5 Conclusion

This research aimed to use realistic dependent synthetic networks to elucidate cascading failure and observe the ensuing behavior. Some extreme-consequence scenarios appear to model what could be considered a black swan event due to the deep uncertainty of their consequences. Others are more representative of perfect storms. Whether synthetic networks reveal black swan events that are plausible in the real world will remain unanswered simply due to the nature of Black Swans – especially since a direct comparison between synthetic models and real networks will likely remain unavailable. But while precise outcomes cannot be extrapolated for the real Phoenix systems, it can be said that systems similar in construct to these synthetic networks may have the potential to experience similar behavior.

As infrastructure continues to face more extreme events at greater frequencies, infrastructure managers must work to give their systems and organizations the requisite complexity for the future (Chester & Allenby, 2022). Among these essential activities is *horizon-scanning,* where infrastructure managers use various analysis tools to look for weak signals that may hint at coming disturbances. Modeling efforts with synthetic networks may provide a useful tool for horizon-scanning exercises. This type of risk analysis is not about predicting the unpredictable (an inherent property of Black Swans). Rather the purpose is ultimately intended to make infrastructure organizations more adaptable and - by extension - the infrastructure network itself (Hoff et al., 2023). These are exercises in searching for unknown unknowns. Although it is impossible to expose all outcomes, the skills gained in such exercises open the minds of infrastructure managers to the existence of Black Swans and – in so doing – give them resilience and reactive tools for the advent of surprises (Alderson et al., 2022).

CHAPTER 5

CONCLUSION

The chapters of this dissertation have discussed how infrastructure resilience can be bolstered via specific organizational competencies as well as horizon-scanning via specific modeling techniques. This final chapter contains a summary of the findings in this dissertation (Section 5.1), presents the key takeaways and how they contribute to furthering resilience for infrastructure (Section 5.2), discusses the boundaries and limitations of this work (Section 5.3), makes proposals for future research opportunities (Section 5.4), and concludes with a candid thought about resilience and infrastructure (Section 5.5).

5.1 Summary

The findings in this dissertation consistently imply that infrastructure organizational resilience is rooted in continuous innovation, creativity, collaboration, and forward-thinking from infrastructure managers rather than from technological improvements. As current events continually overturn the robustness of historical infrastructure standards, it is clear that technological infrastructure systems lack adaptive capacity for the future Anthropocene. Thus, resilience must come from another source.

Dynamic criticality for infrastructure orgnizations is born from the desire to be resilient combined with a dearth in knowledge of how to quickly pivot priorities in times of disorder. Based on the competencies in Chapter 2, infrastructure managers should orient their goals, organizational structures, sensemaking, and strategies toward readiness for rapid shifts in priorities during disturbances. This study revealed that other domains are rife with wisdom for how to work towards dynamic criticality. The four themes and associated competencies are practical and pragmatic for infrastructure managers. Moreover, they are nearly all organizational, requiring minimal technological changes to infrastructure systems. Infrastructure organizations should take account of the disturbance types that they routinely face (i.e., acute, continuous, and hybrid), build relevant strategies, and then rehearse the implementation outside of the disturbance setting for preparedness.

In Chapter 3, an explorarion of potential modeling uses at the nexus of synthetic infrastructure models, interdependent networks, and cascading failure simulations reveals that the insights gained from SICFMs may increase sensemaking capabilities for infrastructure organizations. The findings indicate that the bodies of literature for synthetic power and water systems are robust enough that these models may be used in other research efforts such as scenario analysis, enhanced risk analysis, and black swan scenario elucidation. Researchers in other infrastructure fields besides power and water should consider developing similar synthetic networks to increase the suite of tools available in this space.

Chapter 4 provides an example of how SICFMs might be used to elucidate previously inconceivable scenarios for failure in urban environments. SICFMs distinguish themselves from traditional multi-network cascading failure simulations because they replace most stochastic variables with engineered operations and are deterministic instead of probabilistic – with the disclaimer that an engineered model is not perfectly representative of the real world. So, while the results cannot be used to prescribe system alterations, the realistic nature of the interactions showcases how dependent cascading failure might unfold in similar urban scenarios. These results and future models can inspire engineers, planners, and officials toward novel risk analysis and contingency plans.

5.2 Synthesis: Infrastructure Resilience Demands Constant Reevaluation

5.2.1 Dynamic Criticality as a Resilient State of Existence

The theory of dynamic criticality comes from the physical sciences, describing natural systems that find the perfect balance between robustness and adaptability (Roli et al., 2018). This balance contrasts with irrelevent systems that perish after disturbances exacerbate their weakness (Pascale, 1999). Dynamic criticality for infrastructure managers proposes the same balance. Infrastructure managers might consider attaining this balance between robust and adaptable as a state of being, rather than a discrete event. Unlike many natural manifestations of self-organized criticality (see Bak, 1990), staying in this state requires proactive investment. It is not passive. Notably, remaining in this balance is not the same as optimization, which should be avoided in an age of volatility (Kim et al., 2019). Rather, this should be considered like the differential relationship between velocity and acceleration from kinematics (i.e., $\frac{d}{dt}v_0 + at = a$). If the effort level (i.e., acceleration) to reach dynamic criticality is a positive number, then an organization's movement (i.e., velocity) toward that state will also be positive. However, velocity remains constant if acceleration is zero. With zero acceleration, an organization will be surpassed by the accelerating environment. Likewise, quick pivots in priorities will not occur for infrastructure organizations without serious investment in the necessary skills.

The means to remain in the state of dynamic criticality would then be the competencies that are required. Infrastructure managers should constantly contextualize goals, structures, sensemaking, and strategies to the environment. For example, sensemaking is not a one-time exercise. It is a constant process that organizations use to constantly distill garbled incoming data and transform it into understandable information (C. A. Miller & Munoz-Erickson, 2018; Weick, 1995). Building such habits will develop the capacity to recognize threats as they appear on the horizon – analogous to the critical role of England's shoreline radar outposts during the battle of Britain. The competencies identified in Chapter 2 each fulfill a specific role in preparing organizations to pivot resources when necessary.

Investment in these activities often seems wasteful and neglectful of small but immediate problems facing organizations. Indeed, preparation for extreme disturbances often seems futile because of the low probability of such events (Paté-Cornell, 2012). So, leadership endorsement and enablement are necessary to inspire cultural buy-in (A. M. Helmrich & Chester, 2022; Uhl-Bien & Arena, 2018). Leadership that bridges the gap between innovative thinking and efficient administration unlocks creativity (Rosing et al., 2011; Uhl-Bien et al., 2007b). This innovation and creativity build organizations' adaptability during responses to disturbances (Grote, 2019; B. Lichtenstein & Ashmos Plowman, 2009). Leaders within infrastructure management should be responsible for setting organizational goals, which are tied to dynamic criticality. The findings indicate that goals have an initiating role in tipping an organization toward building the appropriate competencies to approach dynamic criticality.

Finally, if infrastructure organizations do not pursue activities in support of dynamic criticality for their organizations, it is likely that they will become more irrelevant to today's chaotic environment. Infrastructure has already displayed many obdurate attributes, such as in engineering education, adaptive capacity, and consideration of infrastructure as only technological systems (B. Allenby & Chester, 2018; Chester & Allenby, 2021; Markolf et al., 2018). Greater Society will likely continue continue functioning whether infrastructure organizations adapt or not, but adaptations (or lack thereof) may define the societal fallout as disturbances continue to intensify.

5.2.2 SICFMs Need Investment and Contextualization

SICFMs have capabilities that have yet to be fully realized. SICFMs require unified investment from the research community and practitioners to come to fruition. The literature review in Chapter 3 shows abundant progress in synthetic infrastructure modeling, interdependent networks, and cascading failure dynamics. Models that fuse these domains may potentially provide novel insights for infrastructure resilience – particularly in envisioning previously un-imagined Black Swans. Moreover, there are security implications that come with advancements in these models that are important for infrastructure managers to be aware of, regardless of how SICFMs are used.

The advancement of SICFMs hinges on several key developments. It is easy to see that the researchers, SICFMs, and community stakeholders have an interdependent relationship. Infrastructure planners lack tools for risk analysis at fine scales (Hoff & Chester, 2023) and thus rely on developers and researchers for these future tools. In return, researchers need validation and assistance from community stakeholders to develop realistic SICFMs (Ali et al., 2022; Meyur et al., 2020). First, researchers must syndicate synthetic model development outside of academia. But community stakeholders are rarely willing (or even able) to share data that would aid the development of these models (Meyur et al., 2020, 2022). Indeed, critical infrastructure is a national security concern, and researchers should exercise discretion when advancing models and publishing them (see section 5.4.4, Weaponization and Security Considerations). But, frequently, security concerns arise because officials are ignorant of risk within infrastructure, and many infrastructure personnel are untrained and unprepared as a result (Franchina et al., 2021).

Thus, everyone in the infrastructure community is a stakeholder for SICFMs – researchers, utility owners, and community leaders. To fully capitalize on this opportunity, many organizations should invest. Without unified investment, it may be difficult for the models to advance meaningfully.

5.2.3 SICFMs as Catalysts (Not Solutions) for Dynamic Criticality

In essence, SICFMs are a means to move toward a state of dynamic criticality – rather than some predictive or prophetic "crystal ball." Indeed, SICFMs can be a powerful tool to extend risk analysis into previously unexplored regions (Paté-Cornell, 2012); but importantly, they are a tool. Their advent could stimulate new ways that infrastructure managers frame their systems (i.e., as dynamic systems that are interconnected and constantly affected by other systems) (Chester & Allenby, 2019b; A. M. Helmrich et al., 2020). An example: at the time of this dissertation's writing, the novel artificial intelligence (AI) platform ChatGPT has burst into the public limelight, and organizations the world over are all considering how to capitalize on this new capability, while others are concerned that this acceleration will become existential to humanity (Wallace-Wells, 2023). Concerns notwithstanding, AI should not be viewed as anything more than a tool. It cannot solve unprompted problems (yet), but it can be assigned menial tasks that are often time-consuming barriers to investigating deeper questions.

Likewise, SICFMs are tools that visualize scenarios for infrastructure in a quantity and fine-scale that has been previously impossible (Hoff & Chester, 2023). The work presented in Chapter 4 showcases these models' ability to elucidate unlikely but catastrophic events. The discussion on Scenario 22 exemplifies this, as shown in Section 4.4.3. In this scenario, various transmission line failures can lead to large (and different) areas of power and water pressure being lost. Of note, Scenario 22 can converge via multiple line and substation avenues – as opposed to just one, like most of the other high-impact scenarios. This diversity implies a more systemic vulnerability in the synthetic power and water networks. (Note: as already mentioned, vulnerabilities in synthetic systems do not imply the same vulnerabilities in the real system.) It also showcases where weak points of interdependency exist. The cluster of pumps around the WTP is a critical vulnerability that would be mitigated by redundancy in the real world. Nevertheless, it demonstrates that the potential weak point – if not mitigated – would greatly impact Phoenix. These types of "worst case scenarios" could be helpful sensemaking exercises for infrastructure organizations and their stakeholders to develop plans to support and respond to affected populations and develop or change continuity of operations plans.

This initial test of an SICFM demonstrates that the diverse scenarios can spark inspiration for assessing infrastructure networks as they relate to other infrastructure networks. To be sure, many infrastructure managers already spend ample time analyzing their systems for vulnerabilities. But do they (or *can* they) consider interdependence? With some investment and partnership, SICFMs can catalyze such analysis.

5.3 Boundaries and Limitations

This dissertation's work was subject to some firm boundaries and limitations. Each chapter had its unique boundaries, which are discussed in this section. Many of these limitations also inspire future work on these topics, which is discussed in the next section.

Best practices for dynamic criticality can be observed in nearly every facet of society and nature (Roli et al., 2018), and thus, the scope of Chapter 2 had to be limited. The selection of domains for the chapter was primarily limited to those familiar the author. The investigation initially proposed two additional industrial sectors (finance and logistics). However, these sectors were eliminated after very little literature was found during the initial searches. Ultimately, the insights discussed from these sectors are not mutually exclusive to insights from other sectors. But, for brevity, the study was limited to the five domains included in Chapter 2.

The fusion of synthetic infrastructure, interdependent networks, and cascading failure is only one potential use for these three interdisciplinary research fields. Arguments for other uses can be also made using the same literature library from Chapter 3. The selection of SICFMs as a topic of interest came from the dearth of literature discussing the potential uses for synthetic networks. This conversation has not yet occurred within the research community. Nevertheless, synthetic networks continue to be developed. In the case of synthetic power, there is a clear vision and conversation regarding their use as benchmark test networks for many other uses (Marcos et al., 2017;

Mohammadi & Saleh, 2021). However, no vision exists beyond how synthetic networks can be fused with other infrastructures. Wang et al. (2022) was the first study to use synthetic networks to model an interdependent system with exchanging “flows” between then different networks. But cascading failure was not included. Thus, this paper took a first step in what hopefully becomes a larger body of work toward combining synthetic networks for interdependent cascading faiolure.

Constructing an initial test SICFM using existing methodologies came with many challenges. First, Chapter 4 was bounded by the two existing methodologies from Birchfield et al. (2017) and Birchfield & Overbye (2020) for the power system and (Ahmad et al., 2020) for the water system. The primary goal of the methodology selection was to create two networks with approximately equivalent engineering robustness. These two networks used engineering operations to operate themselves and eliminated the necessity for most stochastics, except for the initial failures – which used a Monte Carlo simulation. For the power network, the model does not include any distribution networks. Thus, power outages were limited to substation service regions and could not be approximated at a finer scale. In the water model, there were some notable qualitative differences between the real Phoenix network and the synthetic network. The model as it currently existsClick or tap here to enter text. satisfies pressures at nodes using only pumps and does not use water towers/tanks.

Moreover, while water networks do generally follow roads, as new and old water synthetic models assume (Mair et al., 2014; Momeni et al., 2023; Sharvelle et al., 2017; Sitzenfrei et al., 2010), water tanks do assist in providing localized pressure to some clusters within the network (Kelso, 2022). But since this capability was not available in the Ahmad et al. (2020) model, this difference must be accepted and then considered when interpreting the results of Chapter 4. Additionally, both models were limited to the city limits of Phoenix only because, for this initial study, modeling the whole Phoenix metro area would have been a much higher modeling burden. Moreover, nuances within the power and water networks for the Phoenix metro region may be misrepresented by one simple grid (Kelso, 2022). If the whole metro region is to be modeled in the future, the synthetic network construction methodology may need to be modified.

Lastly, a robust analysis of power and water dynamics was outside the scope of Chapter 4. The research objective for the chapter is to elucidate cascading failure in an urban area and visualize potential extreme events. Thus, a granular analysis of the engineering dynamics within each system would have distracted from the objective. However, follow-on research may use these results to delve deeper into engineering dynamics to improve synthetic, interdependent, and cascading failure modeling techniques.

5.4 Broader Implications and Future Work

5.4.1 Success Stories for Infrastructure Dynamic Criticality

Many infrastructure organizations likely exhibit dynamic criticality in past or present actions, and Chapter 2 does not include any positive examples. Research to find exemplary manifestations of dynamic criticality within infrastructure could provide additional recommendations for infrastructure organizataions. This research could include detailed case studies on one or a few examples or perhaps a broader survey with many examples in diverse infrastructure sectors. For example, Gilrein et al. (2019) identified best practices for transforming infrastructure from rigid to adaptable within multiple infrastructure sectors. A similar study for dynamic criticality may be worthwhile and give infrastructure managers tractable courses of action for the future.

5.4.2 A Common Lexicon for Synthetic Infrastructure

The term “synthetic” is used in modeling for some infrastructure disciplines, but not all of them. Chapter 3 used the term because it was the most common in power and water systems – the two most predominant infrastructures with synthetic models. As previously stated, Mohammadi & Saleh (2021) defined synthetic networks as those possessing three general properties: 1) the representativeness of actual networks, 2) the confidentiality of actual data, and 3) the use of real engineering properties. For some infrastructures, the concept of a fictional-yet-realistic network is just emerging, and the term “synthetic” is not used in their literature. Additionally, “synthetic” is not exclusively used to describe the three attributes above. In some cases, the term has been used to describe a much wider range of infrastructure models, including those that do not attempt to be realistic or detailed (Mahabadi et al., 2021). Therefore, it is important to establish a common lexicon for terminology across disciplines. This discussion should be had between leaders in research fields to harmonize future modeling efforts.

5.4.2 The Water Network

As mentioned in Chapter 4 and in Section 5.3, the methodology used for constructing the synthetic network has some qualitative differences from the real network. First, the model uses a source (the WTP), gravity, and booster pumps (when necessary) to achieve adequate pressure. But, in a large city like Phoenix, water tanks are also placed in elevated locations to provide pressure (Kelso, 2022). Moreover, the Chapter 4 model does not intentionally loop the network but uses roads and a minimum spanning tree approach to reach every node in the network. Coincidentally, Phoenix has been geographically constructed as a grid city, and thus, the WDN for Chapter 4 naturally has loops. But, most other cities in the United States are not constructed as grids, so loops may not occur when using the same methodology. For these reasons, future research may consider modifying the existing model or adopting another method altogether. For example, Momeni et al. (2023) recently published a synthetic water network optimization model that uses resilience and economic optimization parameters while also satisfying pressure in the model.

5.4.3 The Power Network

Future research will offer opportunities to make the power network even more realistic. As mentioned in section 5.4.2, this model was limited to Phoenix to ensure that the water and power networks covered the same geographical region. There would be different insight when observing how power failures cascade across the much larger metro area.

This model did not include power distribution networks to specific nodes. Synthetic transmission and distribution networks are being developed as separate methodologies. But there may be opportunities to combine them in future studies. In one study, distribution and transmission models have been combined to create highly detailed synthetic networks (H. Li et al., 2020). But it is very laborious to fuse these methodologies. Thus far, no research has been conducted on modeling cascading failure dynamics between synthetic transmission and distribution networks. This study focused on transmission initially because, power generation flows through transmission lines initially. However, fusing transmission with distribution in future research could further increase the detail in cascading failures. In Chapter 4, the water network was able to provide outages at specific nodes while the power system was limited to service regions. So, including power distribution in the future may bring the same level of detail to the cascading failure results.

5.4.4 Weaponization and Security Considerations

Developers of SICFMs must not be ignorant of the potential for advanced modeling to highlight strategic vulnerabilities within infrastructure and the reality that geopolitical adversaries will undoubtedly take notice. Infrastructure has always been a strategic consideration in conflict, and the 21st century has amplified this reality (B. R. Allenby, 2016). Today, in cyberspace, the United States is constantly assaulted by foreign adversaries aiming to destabilize and degrade infrastructure for strategic advantage (Arata III & Hale, 2018; Covington & Carskadden, 2013). Models like SICFMs may not predict reality, but they do reflect realistic scenarios for realistically designed systems. Thus, there may only be a small difference between these realistic scenarios and failures that could happen in the real world. As the geopolitical conflict accelerates between the United States and other superpowers, it should be expected that adversaries will seek to destabilize the United States via cyberspace (Brose, 2020; Jakubowski, 2019), and infrastructure will be a primary target (Chester & Allenby, 2020). Thus, care and good cybersecurity practices should be used in future work on SICFM models. Moreover, future conversations should be had around how much (or how little) SICFMs may benefit (or harm) society from a security perspective.

5.4.5 Modeling toward SICFMs

While the model in Chapter 4 is a progressive step toward designing true SICFMs, work still needs to be done. The water and power networks are realistically constructed, meeting the requirement for an SICFM. However, the models in Chapter 4 do not not use a time-series, which prevents them from providing continuous feedback to each other. Instead, the model uses binary dependency conditions, which are less realistic. Realistic interdependencies, as illustrated in Chapter 3, require this real-time feedback to simulate the true behavior of real infrastructure systems.

However, Chapter 4 is a stepping stone to constructing true SICFMs. Chapter 3 found that interdependency modeling has often used theoretical networks – typically not representative of real networks. Additionally, these historical models cannot incorporate engineered design or operation to simulate cascading failure. The model in Chapter 3 satisfies both of these requirements but uses realistically designed networks and engineered operations for cascading failure. The power network uses contingency analysis for power balancing to determine failure. The water network uses EPANET to simulate iterative pressure rebalancing within the water system as pumps lose power. Thus, the model satisfies two of the three primary requirements for SICFMs. Additional research should be done to add time-series simulations to the power and water networks. This progress would enable more realistic feedback and the exchange of resources between the two networks (Varga et al., 2014). Time-series operations would also allow for time-based demands, which can add dynamic behavior to the system, such as peak loads in the evening (Y. Wang et al., 2022).

5.5 A Closing Thought About This Work, Infrastructure, and Resilience

Infrastructure will undergo a monumental paradigm shift in the coming century. The strain of the Anthropocene will demand it. The question remains whether infrastructure organizations will embrace this shift or adjust slowl; and the answer to this question will likely determine the nature of outcomes to society – positive or negative. What this work reveals is that infrastructure organizations and the management of their systems ultimately determine infrastructure resilience. Chapter 2 discusses how infrastructure organizations must first build organizational capacity to prioritize critical assets and manage them effectively. Chapter 3 discovers that stakeholder investment is more crucial to modeling networks for resilience insights. Chapter 4 finds that, while SICFMs are tools to analyze infrastructure systems, they are essentially a sensemaking exercise for infrastructure organizations to use for capacity-building (i.e., dynamic criticality). Ultimately, SICFMs use foundational scientific principles in an applied setting and then seek to translate them into a contextualized format that is useful to build stronger and more resilient infrastructure systems and organizations.

Taleb (2014), in the book *Antifragile*, discusses the idea that there are things in this world that "gain from disorder." Among his examples is a person named "Fat Tony," who made an absurd amount of money when he bet against the stock market before the 2008 recession in the United States. Some people saw Tony's win as a lucky break. But Taleb points out that Fat Tony understood the nature of complex human networks: they are fragile, and failures are inevitable. Likewise, infrastructure managers have opportunities to act based on the inherent fragility within their wickedly complex systems and the inevitability of disturbances to come. Expecting disturbance-induced failure is not a pessimistic viewpoint; rather, it is realistic. This realism can – and should – be a compelling driver for changes toward the concepts researched in this dissertation and other resilience changes for infrastructure.

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APPENDIX A

CO-AUTHOR PERMISSION FOR PUBLISHED MATERIAL

Chapter 2 has been published in *Environmental Research: Infrastructure and Sustainability* and appears as published except for text and figure formatting. All Co-Authors of Chapter 2 have granted permission for use of the material in this dissertation. The citation for this article is:

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* * *

Chapter 3 has been submitted to *Environmental Research: Infrastructure and Sustainability*. The submittal has been reviewed and returned for minor corrections, which are being addressed at the time of this dissertation submittal. Thus, there will be some minor differences between this chapter and the final version of the published article. The full author list is Ryan Hoff, and Mikhail Chester. All Co-Authors have granted permission for use of the material in this dissertation.

* * *

Chapter 4 appears as a manuscript in preparation for submittal to an academic journal. The anticipated author list is Ryan Hoff, Ryan Sparks, Rui Li, Adam Birchfield, Nasir Ahmad, Nathan Johnson, and Mikhail Chester.

APPENDIX B

SUPPLEMENTAL DATA FOR CHAPTER 4

Table B.1 – Substation Frequency of Failure for Chapter 4

Sub Name	*Frequency of Failure (of 21234)*	*115% TH*	*135% TH*	*245% TH*
PHOENIX_1	322	157	93	72
PHOENIX_2	540	319	146	75
PHOENIX_3	0	0	0	0
PHOENIX_4	438	270	120	48
PHOENIX_5	281	155	63	63
PHOENIX_6	0	0	0	0
PHOENIX_7	80	54	13	13
PHOENIX_8	349	313	35	1
PHOENIX_9	0	0	0	0
PHOENIX_10	0	0	0	0
PHOENIX_11	0	0	0	0
PHOENIX_12	474	158	158	158
PHOENIX_13	150	50	50	50
PHOENIX_14	209	84	65	60
PHOENIX_15	0	0	0	0
PHOENIX_16	11	5	3	3
PHOENIX_17	0	0	0	0
PHOENIX_18	783	323	313	147
PHOENIX_19	263	263	0	0
PHOENIX_20	1107	369	369	369
PHOENIX_21	0	0	0	0
PHOENIX_22	12	4	4	4
PHOENIX_23	1050	595	322	133
PHOENIX_24	531	529	2	0
PHOENIX_25	0	0	0	0
PHOENIX_26	163	74	60	29
PHOENIX_27	25	9	8	8
PHOENIX_28	27	9	9	9
PHOENIX_29	359	207	120	32
PHOENIX_30	306	102	102	102
PHOENIX_31	0	0	0	0
PHOENIX_32	3	3	0	0
PHOENIX_33	13	11	2	0
PHOENIX_34	490	374	91	25
PHOENIX_35	94	92	2	0
PHOENIX_36	0	0	0	0
PHOENIX_37	0	0	0	0
PHOENIX_38	35	32	3	0
PHOENIX_39	0	0	0	0

Sub Name	Frequency of Failure (of 21234)	115% TH	135% TH	245% TH
PHOENIX_40	204	154	50	0
PHOENIX_41	975	814	161	0
PHOENIX_42	2	2	0	0
PHOENIX_43	4	4	0	0
PHOENIX_44	0	0	0	0
PHOENIX_45	66	24	21	21
PHOENIX_46	0	0	0	0
PHOENIX_47	0	0	0	0
PHOENIX_48	0	0	0	0
PHOENIX_49	0	0	0	0
PHOENIX_50	247	89	79	79
PHOENIX_51	72	72	0	0
PHOENIX_52	11	11	0	0
PHOENIX_53	0	0	0	0
PHOENIX_54	274	92	91	91
PHOENIX_55	0	0	0	0
PHOENIX_56	0	0	0	0
PHOENIX_57	0	0	0	0
PHOENIX_58	0	0	0	0
PHOENIX_59	9	8	1	0
PHOENIX_60	26	23	3	0
PHOENIX_61	15	5	5	5
PHOENIX_62	23	14	7	2
PHOENIX_63	6	2	2	2
PHOENIX_64	0	0	0	0
PHOENIX_65	0	0	0	0
PHOENIX_66	0	0	0	0
PHOENIX_67	12	4	4	4
PHOENIX_68	0	0	0	0
PHOENIX_69	0	0	0	0
PHOENIX_70	4	3	1	0
PHOENIX_71	990	330	330	330
PHOENIX_72	0	0	0	0
PHOENIX_73	9	3	3	3
PHOENIX_74	33	20	13	0
PHOENIX_75	2	2	0	0
PHOENIX_76	0	0	0	0
PHOENIX_77	0	0	0	0
PHOENIX_78	0	0	0	0
PHOENIX_79	109	86	22	1

Sub Name	Frequency of Failure (of 21234)	115% TH	135% TH	245% TH
PHOENIX_80	9	8	1	0
PHOENIX_81	0	0	0	0
PHOENIX_82	942	314	314	314
PHOENIX_83	327	279	24	24
PHOENIX_84	3	2	1	0
PHOENIX_85	0	0	0	0
PHOENIX_86	0	0	0	0
PHOENIX_87	3	3	0	0
PHOENIX_88	1026	834	192	0
PHOENIX_89	0	0	0	0
PHOENIX_90	0	0	0	0
PHOENIX_91	1	1	0	0
PHOENIX_92	0	0	0	0
PHOENIX_93	2	0	2	0
PHOENIX_94	0	0	0	0
PHOENIX_95	0	0	0	0
PHOENIX_96	535	525	10	0
PHOENIX_97	83	65	9	9
PHOENIX_98	432	424	7	1
PHOENIX_99	158	156	2	0
PHOENIX_100	1071	357	357	357
PHOENIX_101	0	0	0	0
PHOENIX_102	1401	1340	60	1
PHOENIX_103	0	0	0	0
PHOENIX_104	7	7	0	0
PHOENIX_105	0	0	0	0
PHOENIX_106	0	0	0	0
PHOENIX_107	234	224	10	0
PHOENIX_108	585	454	130	1
PHOENIX_109	20	20	0	0
PHOENIX_110	2	0	2	0
PHOENIX_111	810	270	270	270
PHOENIX_112	673	480	191	2
PHOENIX_113	0	0	0	0
PHOENIX_114	0	0	0	0
PHOENIX_115	0	0	0	0
PHOENIX_116	247	247	0	0
PHOENIX_117	32	32	0	0
PHOENIX_118	0	0	0	0
PHOENIX_119	279	272	7	0

Sub Name	Frequency of Failure (of 21234)	115% TH	135% TH	245% TH
PHOENIX_120	203	92	111	0
PHOENIX_121	0	0	0	0
PHOENIX_122	607	560	47	0
PHOENIX_123	1112	1076	34	2
PHOENIX_124	962	674	285	3
PHOENIX_125	2	2	0	0
West Phoenix	0	0	0	0
Agua Fria	30	29	1	0
Kyrene	6	5	1	0
Palo Verde	0	0	0	0
Waddell	972	324	324	324
Arlington Valley Energy Facility	21234	11697	5704	3833
Red Hawk	0	0	0	0
Luke Solar	1068	356	356	356
Arlington Valley Solar Energy II	2	2	0	0
Mesquite Solar 1	2	2	0	0
Badger 1	3	1	1	1

Table B.2 – Chapter 4 - 100 Most Severe Outages, by Population Without Power

Note 1: all scenarios included some kind water service failure.

Note 2: Scenario 22 is the most frequently occurring, but does not appear until number 26.

Severity Rank (by pop w/o power)	*Failure Threshold %*	*num initial failures*	*num lines cascaded*	*num subst failed*	*Area without Power (sq-km)*	*Pop without Power*	*Scenario Number*	*Nodes without Water*
1	115	4	59	11	80.9	144051	23	2511
2	115	4	34	9	84.2	132167	13	568
3	115	4	37	8	59.5	123118	31	5
4	115	3	33	8	59.5	123118	31	5
5	115	3	33	8	59.5	123118	31	5
6	115	3	32	7	57.7	121649	31	5
7	115	3	32	7	57.7	121649	31	5
8	115	4	32	7	57.7	121649	31	5
9	115	4	49	8	79.8	121266	13	568
10	115	3	38	12	145.6	119555	17	1545
11	115	4	38	12	145.6	119555	17	1545
12	135	4	54	13	128.5	116761	8	521
13	115	3	50	10	97.8	112513	6	3674
14	115	4	50	10	97.8	112513	6	3674
15	115	4	38	7	55.1	112217	31	5
16	115	4	38	7	55.1	112217	31	5
17	115	4	38	7	55.1	112217	31	5
18	115	4	38	7	55.1	112217	31	5
19	115	4	38	7	55.1	112217	31	5
20	115	4	38	7	55.1	112217	31	5
21	115	4	38	7	55.1	112217	31	5
22	115	4	38	7	55.1	112217	31	5
23	115	4	38	7	55.1	112217	31	5
24	115	4	38	7	55.1	112217	31	5
25	115	4	31	8	53.6	110153	22	2867
26	115	4	36	7	53.6	108199	31	5
27	115	3	31	8	52.2	105310	22	2867
28	115	4	48	8	53.9	103188	27	5
29	115	4	41	9	86.9	101251	7	398
30	115	4	31	8	47.3	99796	31	5
31	115	4	21	7	62.2	99121	23	2511

Severity Rank (by pop w/o power)	Failure Threshold %	num initial failures	num lines cascaded	num subst failed	Area without Power (sq-km)	Pop without Power	Scenario Number	Nodes without Water
32	115	4	33	7	48.4	97307	22	2867
33	115	4	33	7	48.4	97307	22	2867
34	115	4	32	7	48.4	97307	22	2867
35	115	3	31	7	48.4	97307	22	2867
36	115	3	31	7	48.4	97307	22	2867
37	115	3	31	7	48.4	97307	22	2867
38	115	4	31	7	48.4	97307	22	2867
39	115	4	31	7	48.4	97307	22	2867
40	115	4	30	7	48.4	97307	22	2867
41	115	3	29	7	48.4	97307	22	2867
42	115	4	29	7	48.4	97307	22	2867
43	115	4	29	7	48.4	97307	22	2867
44	115	4	29	7	48.4	97307	22	2867
45	115	4	29	7	48.4	97307	22	2867
46	115	3	28	7	48.4	97307	22	2867
47	115	3	28	7	48.4	97307	22	2867
48	115	3	28	7	48.4	97307	22	2867
49	115	3	28	7	48.4	97307	22	2867
50	115	3	28	7	48.4	97307	22	2867
51	115	3	28	7	48.4	97307	22	2867
52	115	3	28	7	48.4	97307	22	2867
53	115	3	28	7	48.4	97307	22	2867
54	115	3	28	7	48.4	97307	22	2867
55	115	3	28	7	48.4	97307	22	2867
56	115	3	28	7	48.4	97307	22	2867
57	115	4	28	7	48.4	97307	22	2867
58	115	4	28	7	48.4	97307	22	2867
59	115	4	28	7	48.4	97307	22	2867
60	115	4	28	7	48.4	97307	22	2867
61	115	4	28	7	48.4	97307	22	2867
62	115	4	28	7	48.4	97307	22	2867
63	115	4	28	7	48.4	97307	22	2867
64	115	4	28	7	48.4	97307	22	2867
65	115	4	28	7	48.4	97307	22	2867
66	115	4	28	7	48.4	97307	22	2867
67	115	4	28	7	48.4	97307	22	2867
68	115	4	28	7	48.4	97307	22	2867
69	115	4	28	7	48.4	97307	22	2867

Severity Rank (by pop w/o power)	Failure Threshold %	num initial failures	num lines cascaded	num subst failed	Area without Power (sq-km)	Pop without Power	Scenario Number	Nodes without Water
70	115	4	28	7	48.4	97307	22	2867
71	115	4	28	7	48.4	97307	22	2867
72	115	4	28	7	48.4	97307	22	2867
73	115	4	28	7	48.4	97307	22	2867
74	115	4	28	7	48.4	97307	22	2867
75	115	4	28	7	48.4	97307	22	2867
76	115	2	27	7	48.4	97307	22	2867
77	115	2	27	7	48.4	97307	22	2867
78	115	2	27	7	48.4	97307	22	2867
79	115	2	27	7	48.4	97307	22	2867
80	115	2	27	7	48.4	97307	22	2867
81	115	2	27	7	48.4	97307	22	2867
82	115	2	27	7	48.4	97307	22	2867
83	115	2	27	7	48.4	97307	22	2867
84	115	2	27	7	48.4	97307	22	2867
85	115	2	27	7	48.4	97307	22	2867
86	115	2	27	7	48.4	97307	22	2867
87	115	2	27	7	48.4	97307	22	2867
88	115	2	27	7	48.4	97307	22	2867
89	115	2	27	7	48.4	97307	22	2867
90	115	2	27	7	48.4	97307	22	2867
91	115	2	27	7	48.4	97307	22	2867
92	115	2	27	7	48.4	97307	22	2867
93	115	2	27	7	48.4	97307	22	2867
94	115	2	27	7	48.4	97307	22	2867
95	115	2	27	7	48.4	97307	22	2867
96	115	2	27	7	48.4	97307	22	2867
97	115	2	27	7	48.4	97307	22	2867
98	115	2	27	7	48.4	97307	22	2867
99	115	2	27	7	48.4	97307	22	2867
100	115	2	27	7	48.4	97307	22	2867