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INFRASTRUCTURE NETWORK RESILIENCE AND ECONOMIC IMPACTS: APPLICATIONS IN MULTI-MODAL FREIGHT TRANSPORTATION

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INFRASTRUCTURE NETWORK RESILIENCE AND ECONOMIC IMPACTS:
APPLICATIONS IN MULTI-MODAL FREIGHT TRANSPORTATION

A DISSERTATION APPROVED FOR THE
SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

BY

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To

My mother my angel, my father my hero

and my lifelong mentor Aghajoon

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ABSTRACT

The US has defined a number of critical infrastructures, the disruption of which "would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters". Among these critical infrastructures are transportation networks, which enable the flow of people and commodities, and recent reports suggest that many highways, bridges, and other transit assets in the US fall short of a state of good repair, potentially threatening the efficiency of the network. In 2013, 55 million tons of goods valued at more than $49.3 billion traversed the US freight transportation system each day, and freight tonnage and monetary value rose by 6.3 and 8.0 percent, respectively, over 2007 levels. Over the next 30 years, transportation's contribution to the US gross domestic product is expected to grow to approximately $1.6 trillion. Given the potential for disruption by malevolent attacks, natural disasters, human-made accidents, or common failures, recent US planning documents focus on the criticality of transportation network preparedness. Emphasis has been placed on "securing and managing flows of people and goods" along transportation networks. The consequences of disruptions to critical infrastructures highlight the need to better understand resilience, or the ability to withstand the effects of and recover timely from a disruption. Particularly for critical infrastructures, the Infrastructure Security Partnership (2011) noted that a resilient infrastructure sector would "prepare for, prevent, protect against, respond or mitigate any anticipated or unexpected significant threat or event" and "rapidly recover and reconstitute critical assets, operations, and services with minimum damage and disruption." As with any other critical infrastructure, resilience planning is important for multi-modal transportation networks due to their role in the economic vitality of states, regions, and the broader country. The functionality of this network is threatened by disruptive events that can disable the capacity of the network to enable flows of commodities in portions of nodes and links.

This research creates a new paradigm with which to improve decision making for freight transportation network sustainment through an integrated duple of *resilience* and *interdependent economic impact*. Integrating a multi-commodity network flow formulation with an economic interdependency model, driven by publicly available data from Bureau of Economic Analysis and U.S. Department of Transportation, I have proposed a framework to quantify the multi-regional, multi-industry impacts of a disruption in the transportation network which has led to (i) defining a new measure of network component importance, (ii) planning for adaptive capacity through contingent rerouting, (iii) investing for absorptive capacity, and (iv) guiding network recovery and resilience. This work has been applied a multimodal freight transportation network in Oklahoma that connects the state to several regional trading states, enabling the flow of six important commodities that have interdependent effects on the Oklahoma economy (classified into 62 industry sectors).

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CHAPTER 1

INTRODUCTION AND MOTIVATION

1.1 Overview

In response to the growing vulnerability of critical infrastructure given their exposure to natural hazards, malevolent attacks, and the challenges of aging, the Presidential Policy Directive on Critical Infrastructure Security and Resilience (PPD-21) (White House 2013) was established to focus national efforts to enhance the critical infrastructure network resilience.

The Nation's critical infrastructure provides the essential services that underpin American society. Proactive and coordinated efforts are necessary to strengthen and maintain secure, functioning, and resilient critical infrastructure – including assets, networks, and systems – that are vital to public confidence and the Nation's safety, prosperity, and well-being.

- Presidential Policy Directive/PPD-21: Critical Infrastructure Security and Resilience (The White House 2013)

Among the critical infrastructures defined by the US government are transportation networks, which are vital to a society and support many economic activities including commerce and tourism. Disruptions triggered by natural hazards, human-made events, or common failures can severely compromise a region’s ability to move people and commodities, consequently leading to irrecoverable economic losses as well as public safety concerns. Many recent large-scale examples highlight the growing need to deal with disruptions: Hurricane Sandy that affected multiple infrastructure networks, including downed power lines and massive flooding on New York and New Jersey roadways and one million cubic yards of debris that impeded transportation networks (Lipton 2013); the August 2003 US electric power blackout that caused transportation network disruptions (Minkel 2008); and Hurricane Isabel that adversely impacted the transportation system of the Hampton Roads, VA region in 2003 and overwhelmed emergency response (Smith and Graffeo 2005). The current state of disrepair of the US transportation network (e.g., roads given an American Society of Civil Engineers Infrastructure Report Card grade of D, bridges a C+, inland waterways a D- (ASCE 2013a)) could make the network especially vulnerable to a disruptive event. The situation is no better for the state of Oklahoma, where bridges in particular received a lower letter grade of D+, which by definition is interpreted as a "poorly performing" infrastructure (ASCE 2013b). Recent US planning documents focus on transportation network preparedness (The House Committee on Transportation and Infrastructure 2013, US Department of Transportation 2014, Yusta et al. 2011), emphasizing "securing and managing flows of people and goods" along transportation networks (DHS 2014).

The physical freight transportation network of the US, the largest in the world, consists of four million miles of public roads, 140,000 miles of railroad tracks, 11,000 miles of navigable waterways, and a network of airports with the combined ability of shipping almost 68,000 tons of cargo per year (U.S. Department of Transportation 2013). Furthermore, the same document highlights the importance of the US transportation network in facilitating the convenient movement of resources among suppliers, manufacturers, wholesalers, and customers, with more than 300 million people and 7.5 million organizations across 3.8 million square miles being served. The vital role the freight network plays in transporting raw materials and final products between manufacturers and consumers highlights its position in commerce. The functionality of this network is threatened by disruptive events that can disable the capacity of the network to enable flows of commodities and cause an interruption of economic productivity across multiple industries. That is, the ultimate usefulness of understanding transportation network disruptions is not just a descriptor of physical damage, but of economic interruption due to infrastructure inoperability (Tierney 1997, Webb et al. 2000). As such, discussions of transportation network resilience should account for multi-industry impacts.

This work focuses on the freight transportation network, particularly on its role of enabling the flow of commodities and facilitating economic productivity, and thus a methodological approach to measure network resilience in the context of multi-industry impacts is sought. That is, this work seeks to answer: how can we enhance freight transportation network resilience? This research addresses (i) measuring the vulnerability of a multimodal freight transportation network with multi-industry impacts in mind, (ii) using the vulnerability analysis to develop a measure of importance for each network component, (iii) planning for adaptive capacity, (iv) investing for absorptive capacity in critical infrastructures and industry sectors, (v) planning network restoration following a disruption.

1.2 Freight Movement and Disruption

To model a supply-demand network for a set of business economic areas consisting of different industries interacting with their suppliers and customers located outside of their region through a multi-modal freight transportation system, a typical multi-commodity network flow (MCNF) model (e.g., Ahuja et al. (1993)) is used. The goal of this model is to facilitate the commodity flows between suppliers and consumers through a capacitated transportation network while minimizing the cost of transportation. Planning decisions in a multi-modal freight transportation network is made at strategic, tactical, and operational levels (Crainic and Laporte 1997). It is assumed that (i) strategic decisions determine general development policies and define the operating strategies of the system over relatively long time horizons (e.g., the location of the physical transportation network, the location of main facilities such as rail yards or multi-modal platforms (Liotta et al. 2015)), (ii) tactical plans deal mostly with medium-term decisions (e.g., route choice and type of service to operate, aggregate scheduling (Kengpol et al. 2012)), and (iii) operational level decisions are made when real or near real-time response is required (e.g., crew or container scheduling (Wang and Yun 2013)).

Natural hazards, human-made events, or common failures could threaten the functionality of the network components and consequently interrupt commodity flows. A common theme in the analysis and evaluation of network vulnerability is interdiction (Gedik et al. 2014, Murray et al. 2008, Murray et al. 2007), in which scenario-based removal of network components is assumed to represent the effects of a disruptive event. The consequences of a targeted attack, accident, or natural disaster are simulated as disruptions in the flow of valuable goods or services through the network caused by disabling network components. The network is analyzed to determine how vulnerable it is to a disruption, and which nodes or links, if lost, result in the most damage to network performance. Further, the temporal and spatial scales at which analysis is conducted, as well as the duration of the disruptive event, affect the disruption analysis.

Approaches to interdict a network differ based on how disruption scenarios are assessed and understood. A disruption scenario is defined by the set of network components that are impacted, the degree to which they are disabled, and the operating conditions (e.g., network activity and link/node capacities) of the network prior to the disruption regardless of the initiating event that causes the disruption. In extreme cases, an affected facility may be rendered completely inoperable by a disruption (e.g., losing a road completely due to a bridge collapse as in the case of the I-35 Mississippi River bridge failure in 2007). In other instances, a disruption may impact network activity to a lesser degree given that only some of the functionality of a facility may be lost (e.g., an accident blocking a single lane of an interstate highway segment). The identification of disruption scenarios enables an impact assessment. Impacts can range from those directly associated with network operation, such as connectivity, flow, or capacity reduction, to more complex associations, such as the economic impacts affecting the production and consumption of flows (Matisziw and Murray 2009).

The flexibility in defining scenario-specific disruptions based on historical data or other desired analysis makes it appropriate for network vulnerability studies. In particular, it provides opportunities for understanding a component's role and importance within a network. For example, one might be interested in the impact of the closure of a bridge or a road segment on network performance (e.g., the flow of commodities, the topological behavior of a post-disruption network, the multi-industry economic impacts). A deterministic scenario-specific approach (Murray et al. 2008), where the potential ramifications of the removal of a particular network component is evaluated, is often used to quantify network component importance measures (e.g., Nagurney and Qiang 2008, Jenelius et al. 2006). Stochasticity could be introduced to capture uncertainty in disruptive scenarios (e.g., Miller-Hooks et al. 2012, Burgholzer et al. 2013, Baroud et al. 2014).

1.3 Interdependent Economic Impact

To model the interdependent adverse effect of commodity flow disruption on multiple industry sectors located in different regions, we use a multi-regional extension of Inoperability Input-Output Model (IIM). The IIM is an extension of the traditional economic input-output model (Leontief 1986), a linear model of the commodity flows in a set of interconnected industries. A risk-based multi-regional interdependency model used to measure the economic impacts of a transportation disruption in terms of remaining commodities at suppliers and unmet demands at demand nodes. The input-output (I-O) model is a widely accepted model for analyzing the interdependent connections among industries (Miller and Blair 2009), and the use of the I-O enterprise for studying disruptions was among the *10 Most Important Accomplishments in Risk Analysis: 1980-2010* (Greenberg et al. 2012).

Despite of the I-O model's assumption of a linear relationship of commodity flows among industries, the extensive usage of I-O models is due in part to the availability data describing the parameters of the I-O model in a number of countries (OECD 2011, Timmer et al. 2015). This includes a data collection effort by the US Bureau of Economic Analysis (BEA), which maintains input-output tables at different levels of aggregation (BEA 2010). Extending the capability of the I-O model, Santos and Haimes (2004) propose the Inoperability Input-Output Model (IIM) to represent the propagation of inoperability, or the proportional extent to which industries are unproductive after a change in demand or a forced change in demand due to a lack of supply. The use of the

IIM can model inoperability in an economic setting, or in a set of interdependent infrastructures (Setola and De Porcellinis 2008, Crowther and Haimes 2010, Oliva et al. 2014). The IIM and some extensions have been deployed in a number of contexts, including analyses of infrastructure disruptions (Anderson et al. 2007, Pant et al. 2011, 2015, Jonkeren et al. 2015, Mackenzie et al. 2012), workforce losses (Orsi and Santos 2010a,b), and supply chain risk (Barker and Santos 2010a,b), among others. Furthermore, the IIM has been used in multi-industry vulnerability studies (e.g., Yu et al. (2014) developed a multi-perspective approach for vulnerability decomposition with the aim of prioritizing key economic sectors in the aftermath of disruptive events).

1.4 Modeling Network Resilience

Several definitions of *resilience* have been proposed, including the ability to withstand, adapt to, and recover from a disruption, a definition with which many would largely agree (The White House 2011). Barker et al. (2013) highlight two important dimensions of resilience: (i) *vulnerability*, or the extent to which the performance of a system degrades after an initiating disruption, and (ii) *recoverability*, or the ability of a system to return to a desired performance level in a timely manner. These are similar to the concepts of *robustness* and *rapidity* in the resilience triangle literature (Bruneau et al. 2003). Similarly, Vugrin and Camphouse (2011) defined the *resilience capacity* of a system as a function of: (i) *absorptive capacity*, or the extent to which a system is able to absorb shocks from disruptive events, (ii) *adaptive capacity*, or the extent to which a system can quickly adapt after a disruption by temporary means, and (iii) *restorative capacity*, or the extent to which the system can recover from a disruption or be reconstructed in the long-term. As such, absorptive, adaptive, and restorative capacities can be viewed as first, second, and third lines of defense, respectively (Hosseini and Barker 2016). Figure 1.1 highlights the relationship between (i) vulnerability and recoverability and (ii) absorptive, adaptive, and restorative capacities.

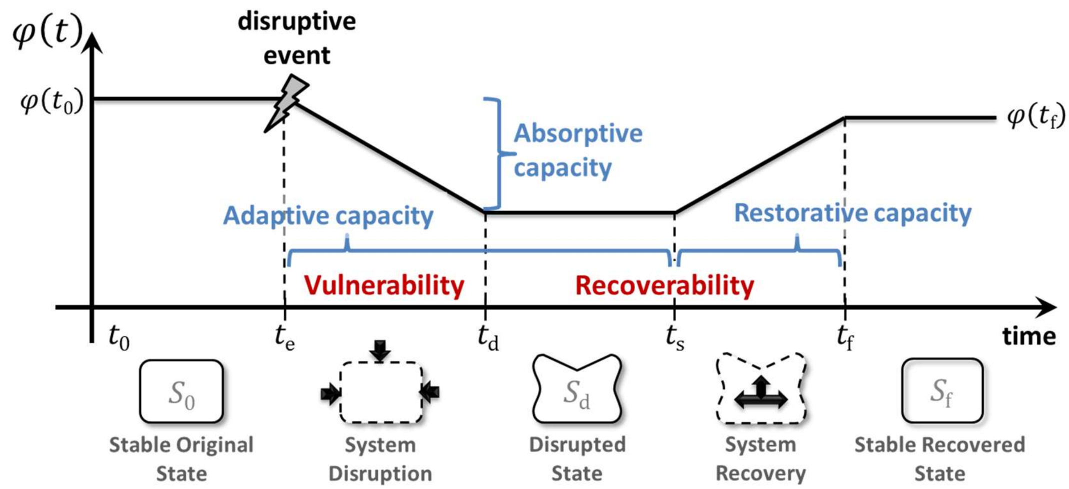


Figure 1.1. The relationship between (i) the vulnerability and recoverability dimensions of resilience and (ii) the components of absorptive capacity with respect to system performance $\boldsymbol{\varphi(t)}$.

1.5 Structure of the Dissertation

Following the introduction presented in Chapter 1, Chapter 2 presents a framework developed to measure the network vulnerability from the unique perspective of multi-industry impacts. The framework is illustrated with a case study considering a multi-modal freight transportation network consisting of inland waterways, railways, and interstate highways that connect the state of Oklahoma to other surrounding states.

In Chapter 3, it is sought how investing in hardening both the infrastructure (e.g., backup equipment) and industries themselves (e.g., on-hand inventory) can lessen the effects of disruptions. Chapter 4 of this dissertation is to devise contingent rerouting plans to strengthen the network's adaptive capacity. And, in Chapter 5, network restoration activities, in terms of the order in which disrupted components should be recovered to enhance the economic productivity, are discussed. Finally, in Chapter 6, concluding remarks and future research avenues are discussed.

CHAPTER 2

FREIGHT TRANSPORTATION NETWORK VULNERABILITY

2.1 Introduction

Presidential Policy Directive 21 states that critical infrastructure "must be secure and able to withstand and rapidly recover from all hazards" (The White House 2013). This combination of the ability to (i) withstand the effects of a disruption and (ii) recover timely from the disruption is often referred to as *resilience* (Hosseini et al. 2016). Figure 2.1. highlights these two dimensions of resilience: vulnerability and recoverability (Henry and Ramirez-Marquez 2012, Pant et al. 2014). The network service function $\varphi(t)$ describes the behavior or performance of the network at time t (e.g., $\varphi(t)$ could describe traffic or commodity flow in a transportation network). The vulnerability dimension of resilience is the focus of this work.

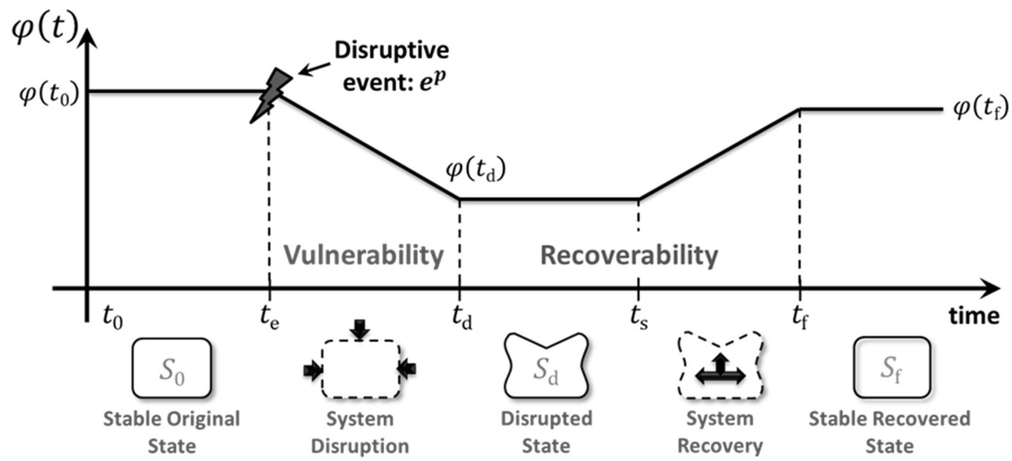


Figure 2.1. System performance, $\varphi(t)$, trajectory following a disruptive event (source: Henry and Ramirez-Marquez (2012)).

In a freight transportation network, vulnerability is considered to be a problem of interrupted serviceability or accessibility of network components, leading to reduced system functionality (Berdica 2002, Chen et al. 2007). O'Kelly (2014) classifies network vulnerability into link vulnerability, or the reduction of a network's capability after losing a link, and nodal vulnerability, or the extent to which a node plays a critical role in the operation of the whole network. From the network interdiction literature, where network components (nodes or arcs) are disabled intentionally, there are three approaches to evaluate network vulnerability (Murray et al. 2008): (i) scenario-specific evaluation, where the potential consequences of a specific disruptive scenario or set of scenarios is evaluated (e.g., studying the impact of losing a bridge, a road segment, or a hub on network performance (Jenelius and Mattsson 2012, Burgholzer et al. 2013, Rupi et al. 2014, Fotuhi and Huynh 2017)), (ii) strategy-specific assessment, where vulnerability is assessed with respect to a hypothesized sequence or strategy of disruptions targeting components perceived to be important (e.g., Erath et al. 2010, Park et al. 2011, Knoop et al. 2012), and (iii) mathematical modeling assessment (e.g., Sullivan et al. 2010, Jenelius et al. 2010), using game-theoretical techniques to find worst-case scenarios. In our work, to analyze network vulnerability and define a measure of importance for network components, a scenario-specific approach is taken by analyzing the proportional effect on the flow of commodities given the removal of one node/link at time.

Most work in network vulnerability focuses on network behavior after a disruption in terms of graph theoretic measures, such as average shortest distance, network diameter, average edge betweenness, and cluster efficiency (e.g., Albert and Barabasi 2002, Jonsson et al. 2008, Chen et al. 2010, Mishkovski et al. 2011, Johansson et al. 2013), which describe what is commonly referred to as structural vulnerability. This is different from functional vulnerability, where operational characteristics (e.g., network flow) of different components are taken into consideration (Ouyang et al 2009). To capture the functional aspects of network vulnerability, a measure of importance for network components was introduced by Nagurney and Qiang (2008, 2007a,b) based on network performance/efficiency considering demands, costs, and flows, as well as behavior of the users of the network. Following the lead of Nagurney and Qiang, the emphasis of this work deals with describing network vulnerability with respect to flow along the network, a more tangible approach than focusing solely on topological features of the network and amenable to an analysis of multi-industry economic impacts. That is, $\varphi(t)$ is used to describe the flow along the transportation network. Further literature describing network component importance based on flow measures is sparse (Rocco et al. 2010, Nicholson et al. 2016), and, to the authors' knowledge, the methodology proposed in this work for pinpointing the contribution and importance of individual transportation network components to multi-industry economic impacts is an area that has not been previously pursued in the literature.

This chapter considers network vulnerability as a relative drop in the commodity flows along the network after the removal of a particular node or link. And a drop in the flow of commodities would generate subsequent impacts on multiple industries relying on those commodities. While several approaches have been proposed to capture interdependencies among infrastructure and industries (Pederson et al. 2006, Haimes 2009, Rose et al. 2012, Ouyang 2014), this work makes use of an economic input-output model extension that quantifies the propagation of multi-industry inoperability (the extent to which industry output will not be produced) caused by perturbations in supply and/or demand.

2.2 Research Methodology

Despite the excellent use of network-based models in representing interdependencies which consider various aspects of network vulnerability (Holden et al. 2013, Miller-Hooks et al. 2012, Pederson et al. 2006), there exists a need to integrate parts of these models with multi-industry impacts to address freight transportation functionality as enabling the flow of commodities and facilitating economic productivity. This need is addressed with a four-step methodology, as illustrated in Figure 2.2, which then culminates in a transportation network component importance measure.

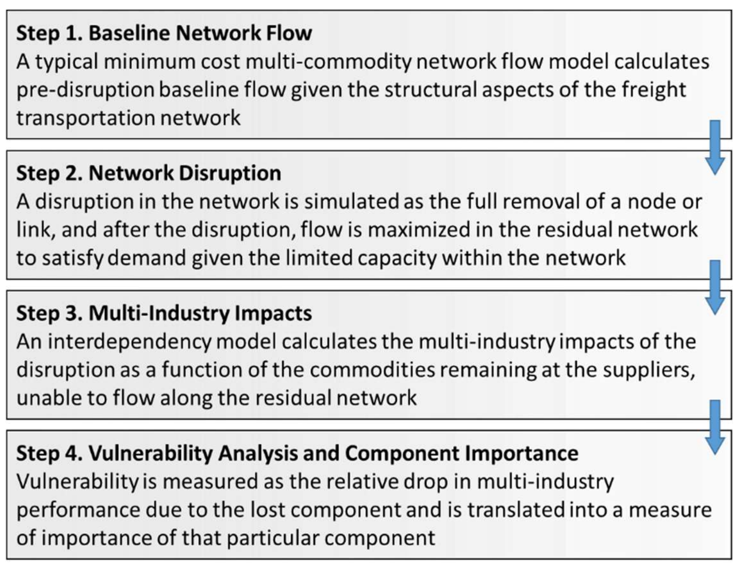


Figure 2.2. Four step approach to assessing transportation component importance with multi-industry impacts.

2.2.1 Baseline Network Flow

To study the vulnerability of a multi-modal freight transportation network, which serves as a facilitator of n interacting industries, the topology of the network and corresponding supply and demand nodes must be extracted. The conventional MCNF problem for a network, $G(N, L)$ with a set of nodes, N, a set of links, L, and a number K of commodities, is formulated in model M1. The flow of commodity k on link (i, j) is represented with f_{ij}^k, and the cost of shipment for commodity k on link (i, j) is w_{ij}^k. The capacity of link (i, j) is represented with u_{ij}, and the supply/demand of commodity k at node i is represented with b_i^k, defining the "bundle" and "mass balance" constraints in model M1, respectively. Note that b_i^k is positive for supply nodes, negative for demand nodes, and zero for transshipment (or intermediate) nodes. The capacity of each link is considered as a shared constraint for all commodities flowing on the link.

$$
\begin{aligned}
min \quad & \sum_{(i,j)\in L} \sum_{k} w_{ij}^k f_{ij}^k \\
s.t. \quad & \sum_{k} f_{ij}^k \le u_{ij} \; \forall \, (i,j) \in L \\
& \sum_{(i,j)\in L} f_{ij}^k - \sum_{(j,i)\in L} f_{ji}^k = b_i^k \;\; \forall \, i \in N, k = 1, \dots, K \\
& f_{ij}^k \ge 0, \forall \, (i,j) \in L, k = 1, \dots, K
\end{aligned}
\qquad \text{(M1)}
$$

In fact, a generic MCNF model provides a means to formulate the supply-demand network in which a multi-modal freight transportation network connects industries and enables trading relationships and interactions. From a tactical point of view, the integration of (i) business economic sectors and (ii) their supply capabilities or demand requirements together with (iii) the structure of the transportation network can result in a minimum cost MCNF model that can route the commodities from suppliers to the demand nodes via f_{ij}^k, collectively representing the flow of commodities on the links of a baseline (undisrupted) network.

2.2.2 Network Disruption

This step evaluates the effect of losing a network component on freight flow through the network and resulting consequences on supply/demand nodes. Hence, a disruptive scenario is defined as the removal of a particular network component. An optimization formulation is developed to reroute commodity flows through the residual network, pursuing the maximum flow throughout the network and capturing failure in the form of remaining commodities at supply nodes and unmet demands at demand nodes, as formulated in model M2. Intuitively, a decision maker would likely desire to reroute commodities to take advantage of the remaining capacity of the residual network. Note the difference in perspective in the post-disruption MCNF developed here: prior to the disruption, model M1 minimizes the cost of transporting commodities along the capacitated network, where model M2 maximizes the flow to meet as much demand as possible given the interrupted network with an updated set of links, L', and nodes N'. To capture undelivered commodities remaining with the suppliers or unsatisfied demand at demand nodes, a slacL',k variable S_i^k is defined. The magnitude of S_i^k is positive, and multiplier γ_i takes on a negative value for the set of demand nodes (after disruption) N'_-, a positive value for supply nodes (after disruption) N'_+, and zero for transshipment nodes (after disruption) N'_0. The objective function maximizes the sum of commodity-specific flows, where f'^k_{ij} represents the flow of commodity k across link (i, j) which remains in the updated set of links, L'. Slack variable S_i^k will be used in the next step to calculate inoperability among multiple industries. Here it is assumed that each type of commodity represents an industry, and interdependent inoperability propagated through the entire regional economy caused by unsatisfactory levels of demands/supplies will be pursued in the next step.

$$
\begin{aligned}
& max \quad \sum_{(i,j)\in L'} \sum_{k} f_{ij}^{\prime k} \\
& s.t. \quad \sum_{k} f_{ij}^{\prime k} \leq u_{ij}' \ \forall\ (i,j) \in L' \\
& \qquad \sum_{(i,j)\in L'} f_{ij}^{\prime k} - \sum_{(i,j)\in L'} f_{ji}^{\prime k} + \gamma_i S_i^k = b_i^{\prime k} \ \ \forall\, i \in N', k = 1, \dots, K \\
& \qquad \gamma_i = \begin{cases} -1 & for\ i \in N_-' \\ +1 & for\ i \in N_+' \\ 0 & for\ i \in N_0' \end{cases} \\
& \qquad f_{ij}^{\prime k} \geq 0, S_i^k \geq 0 \ \ \forall\ (i,j) \in L', k = 1, \dots, K
\end{aligned}
\tag{M2}
$$

2.2.3 Multi-Industry Economic Impact

When a disruption within the transportation network results in remaining commodities at supply nodes and/or unmet demand at demand nodes, inoperability propagates throughout industries in a region. Without loss of generality, each node within the network is considered to be either a supplier or a consumer of a particular commodity. Each commodity belongs to an industry in the economy as defined by the North American Industry Classification System (NAICS). To represent the multi-industry impacts of unmet demands at demand nodes and remaining commodities at the suppliers' side in the MCNF, an extension of the input-output model is used. The input-output (I-O) model, for which Wassily Leontief (1966) won a Nobel Prize, has been widely accepted as a useful model for analyzing the interdependent connections among industries (Miller and Blair 2009). Under a static equilibrium, the total output of the industry s is distributed to other industries and also satisfies external (consumer) demand. This equilibrium condition is described with $x_k = \sum_{r=1}^{n} z_{kr} + c_k$, where x_k is the total output of industry k, z_{kr} is the flow of commodities produced by industry k and used as input to production in industry r, and c_k is the external demand for industry k. The flow of commodities z_{kr} is assumed to be proportional to the output of industry r ($r \in \{1, \ldots, K\}$ and $r \neq k$), expressed as $z_{kr} = a_{kr}x_r$. Further, it is assumed that each industry produces a sole commodity, such that industry k produces commodity k. The common form of the Leontief input-output model is expressed in Eq. (2.1), where **x** is the vector of industry production outputs, **A** is an industry-by-industry matrix of interdependency coefficients, a_{kr}, and **c** is a vector of final demands. The model shows that total production is made up of industry-to-industry intermediate production, **Ax**, and production to satisfy final demand, **c**. Terms z_{kr}, x_r, and c_k are measured in monetary units.

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{c} \Rightarrow \boldsymbol{x} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}\boldsymbol{c} \tag{2.1}$$

Instead of describing the connections between the interdependent industries in terms of commodity flow dollars, the IIM illustrates how normalized production losses propagate through interconnected industries, providing a different perspective from the traditional I-O model. The IIM is provided in Eq. (2.2), describing the relationships among K industries, resulting in matrices of size $K \times K$ and vectors of length K.

$$\boldsymbol{q} = \boldsymbol{A}^{\star}\boldsymbol{q} + \boldsymbol{c}^{\star} \Rightarrow \boldsymbol{q} = [\boldsymbol{I} - \boldsymbol{A}^{\star}]^{-1}\boldsymbol{c}^{\star} \tag{2.2}$$

Vector **q** is a vector of industry inoperability describing the proportional extent to which as-planned productivity or functionality is not realized following a disruptive event. Inoperability for industry k is defined in Eq. (2.3), where as-planned total output is represented with $\hat{x}_k$ and degraded total output resulting from a disruption is represented with $\tilde{x}_k$. An inoperability of 0 suggests that an industry is operating at normal production levels, while an inoperability of 1 suggests that the industry has become completely inoperable.

$$q_k = (\hat{x}_k - \tilde{x}_k)/\hat{x}_k \iff \boldsymbol{q} = [diag(\hat{\boldsymbol{x}})]^{-1}(\hat{\boldsymbol{x}} - \tilde{\boldsymbol{x}}) \tag{2.3}$$

Normalized interdependency matrix $\mathbf{A}^\star$ is a normalized form of the original $\mathbf{A}$ matrix describing the extent of interdependence among a set of industries. As stated by Eq. (2.4), the row elements of $\mathbf{A}^\star$ indicate the proportion of additional inoperability that are contributed by a column industry to the row industry.

$$a_{rk}^\star = a_{rk}(\hat{x}_k/\hat{x}_r) \iff \boldsymbol{A}^\star = [diag(\hat{\boldsymbol{x}})]^{-1}\boldsymbol{A}[diag(\hat{\boldsymbol{x}})] \tag{2.4}$$

Eq. (2.5) provides the calculation of $\mathbf{c}^\star$, a vector of normalized demand reduction. The elements of $\mathbf{c}^\star$ represent the difference in as-planned demand $\hat{c}_k$ and perturbed demand $\tilde{c}_k$ divided by as-planned production, quantifying the reduced final demand for industry k as a proportion of total as-planned output.

$$c_k^\star = (\hat{c}_k - \tilde{c}_k)/\hat{x}_k \iff \boldsymbol{c}^\star = [diag(\hat{\boldsymbol{x}})]^{-1}(\hat{\boldsymbol{c}} - \tilde{\boldsymbol{c}}) \tag{2.5}$$

For the traditional economic loss metric, losses can be calculated by multiplying each industry's production level in monetary units by its inoperability level: for industry k, $Q_k = x_k q_k$, or for the entire economy of industries, $Q = \mathbf{x}^T\mathbf{q}$. As such, planning decisions can be made with respect to inoperability or economic impact at the industry level, or with respect to economic impact across multiple industries.

The freight transportation network provides a platform for commodity flows between industries. Since the IIM models how demand-related risk in a given industry propagates to other industries due to their interdependent productivity, the multi-industry impact of a disruption to a freight transportation network can be studied when network losses are related to final consumption reduction and inoperability terms as shown in subsequent subsections. The demand-reduction IIM proposed by Santos and Haimes (2004) has been successfully employed to study multi-industry impacts of perturbations in supply and demand (e.g., Resurreccion and Santos (2013), Pant et al. (2011), Haggerty et al. (2008), Lian and Haimes (2006)). However, some (e.g., Kujawski (2006), Kelly (2015)) have questioned the usefulness (and theoretical plausibility) of supply-driven models developed from concepts by Ghosh (1985). Leung et al. (2007) integrated a supply-side price IIM and output-side IIM to address initiating perturbations related to input factors (value added) and to industry output levels, though some aspects of this model may be impractical for integration with supply-demand networks as applied in our proposed approach (though may be effective in modeling disruptions to manufacturing systems, as noted by Kelly (2015)). Here, we translate a disruption in the form of remaining commodities at supply nodes and/or unmet demand at demand nodes into the two IIM metrics of inoperability and final consumption perturbation, based on a demand-reduction IIM implemented by Pant et al. (2011) in modeling supply and demand perturbation caused by a port closure. Pant et al. (2011) considered commodities remaining at suppliers after a disruption to calculate the final consumption perturbation. And the authors considered unmet demands to calculate a "forced" demand reduction, assuming that a disruption decreases the supply of a commodity for a demand node while the final external consumption remains virtually unaffected. In such a case, the demand nodes temporarily sacrifice their internal need for that commodity until it returns to its as-planned supply level, and a surrogate to supply reduction is calculated from the combination of "forced" internal consumption and an output inoperability.

In the following subsections, N^{α} represents the set of nodes within the area of interest α, and $N^{\overline{\alpha}}$ represents the set of nodes outside of the area of interest, such that $N = N^{\alpha} \cup N^{\overline{\alpha}}$. We formulate the economic consequences of a failure within a particular area of interest (e.g., a business economic area, county, state, entire country). As such, the failure in the form of remaining commodities at suppliers and unmet demand at consumers are captured only in the nodes within the area of interest and each of the economic parameters (i.e., $\mathbf{x}$, $\mathbf{c}$, $\mathbf{c}^{\star}$and $\mathbf{q}$) are indicators of the industries specific to the region of interest. To simplify the notation, superscript α is not included for these economic metrics to avoid unnecessary indices.

Modeling Remaining Supply: Transportation facilities operate as facilitators of commodity flows across business economic areas. For a supplier of commodity k located in node i, any transportation network disruption that perturbs its desired export will be considered to be a reduction in final consumption. As modeled in Eq. (2.6), final consumption for industry k includes commodities consumed by industry k itself internally, $(\hat{c}_k)_{int}$, and the amount of external consumption that is exported through the network, $(\hat{c}_k)_G$. It is assumed that the disruption results in losses of commodity flows only through the network, while industry production activities unrelated to the network experience no direct failure but might be affected indirectly by a disruption within the network (due to an interdependent loss of economic productivity). When industry k has difficulty only in exporting commodities, it experiences commodities remaining at supply nodes in the region of interest totaling $\sum_{i \in (N'^{\alpha}_{+} \cap N'_k)} S_i^k$, where N'^{α}_{+} represents the set of nodes that are home to suppliers in the region of interest α after the disruption, as shown in Eq. (2.7). As such, the final consumption perturbation for industries that experience difficulties only in exporting commodities is modeled as the amount of slack divided by as-planned industry output in Eq. (2.8), Note that the supply-demand network may consist of suppliers and consumers located outside of the region of interest, yet failures to these suppliers and consumers are not accounted for in this model.

$$\hat{c}_k = (\hat{c}_k)_{int} + (\hat{c}_k)_G \qquad k \in \{1, \dots, n\} \tag{2.6}$$

$$\hat{c}_k - \tilde{c}_k = \sum_{i \in (N'^{\alpha}_{+} \cap N'_k)} S_i^k \qquad k \in \{1, \dots, n\} \tag{2.7}$$

$$c_k^{\star} = \frac{\sum_{i \in (N'^{\alpha}_{+} \cap N'_k)} S_i^k}{\hat{x}_k} \qquad k \in \{1, \dots, n\} \tag{2.8}$$

Modeling Unmet Demand: As discussed by Pant et al. (2011), the amount of import (input) of industry *k* at demand nodes in the supply-demand network defined as $\sum_{i \in (N'^{\alpha}_{-} \cap N'_k)} -b_i^k$ contributes toward the production activity and the internal consumption of industry *k*. Thus, when industry *k* has difficulty only in importing commodities, it experiences unmet demands in the region of interest totaling $\sum_{i \in (N'^{\alpha}_{-} \cap N'_k)} S_i^k$. This results in the loss of output, $\Delta\hat{x}_k$, representing $(\hat{x}_k - \tilde{x}_k)$, and final internal consumption, $\Delta(\hat{c}_k)_{int}$. Here, $N_{-}^{\prime\alpha}$ represents the set of nodes after disruption located in the geographical area of interest α that are home to consumers of commodity k.

$$\sum_{i\in(N_{-}^{\prime\alpha}\cap N_k^{\prime})} S_i^k = \Delta\hat{x}_k + \Delta(\hat{c}_k)_{int} \qquad k \in \{1,\dots,n\} \tag{2.9}$$

Therefore, for industry k, unmet demand causes an inoperability, q_k, measured as the loss of production in industry k as a proportion of its original production level, as shown in Eq. (2.3) with $\Delta\hat{x}_k/\hat{x}_k$. Also, internal consumption failure, as shown in Eq. (2.6), causes a final consumption perturbation, $c_k^\star$, and is modeled as a measure of the change in the final consumption as a proportion of the original production level in industry k, as shown in Eq. (2.5) with $\Delta\hat{c}_k/\hat{x}_k$. The approach to formulate failure in the form of unmet demand is adapted from the port disruption work of Pant et al. (2011, 2015) and the transportation network vulnerability formulation of Darayi et al. (2017), in which a slack variable S_i^k is defined to capture unsatisfied demand at demand nodes (or undelivered commodities remaining with the suppliers), shown in Eq. (2.10). For the industries experiencing difficulties only in importing their required commodities, there exists a final consumption perturbation, as modeled in Eq. (2.11).

$$\frac{\Delta\hat{c}_k}{\hat{x}_k} = \frac{\sum_{i\in(N_{-}^{\prime\alpha}\cap N_k^{\prime})} S_i^k - \Delta\hat{x}_k}{\hat{x}_k} \qquad k \in \{1,\dots,n\} \tag{2.10}$$

$$c_k^\star = \frac{\sum_{i\in(N_{-}^{\prime\alpha}\cap N_k^{\prime})} S_i^k}{\hat{x}_k} - q_k \qquad k \in \{1,\dots,n\} \tag{2.11}$$

Eqs. (2.8) and (2.11) combined with the IIM in Eq. (2.2) form a complete solvable system that quantifies the inoperability and final consumption perturbations for the collection of K interconnected industries. For simplicity, the demand perturbations in Eqs. (2.8) and (2.11) assume failure in either only demand nodes or only supply nodes within a particular industry, whereas in actual situations, some industries would likely consist of both supply and demand nodes. Therefore, the total final consumption perturbation for industry k, in the case of having both importing (demand) and exporting (supply) roles, is given in Eq. (2.12).

$$c_k^\star = \frac{\sum_{i \in (N_+'^{\alpha} \cap N_k')} S_i^k}{\hat{x}_k} + \frac{\sum_{i \in (N_-'^{\alpha} \cap N_k')} S_i^k}{\hat{x}_k} - q_k \qquad k \in \{1, \dots, n\} \qquad (2.12)$$

Any of Eqs. (2.8), (2.11), or (2.12) captures the perturbation vector $\mathbf{c}^\star$ that parameterizes the interdependency model in Eq. (2.2) based on the exporting or importing nature of the nodes belonging to each industry. Thus, $\mathbf{q}$ can then be calculated to measure the proportional extent to which as-planned productivity or functionality is not realized following a transportation network disruption that results in unmet demand or commodities remaining with suppliers, and a contingent rerouting strategy can be devised during the period of disruption to lessen the multi-industry impact of the disruption.

2.2.4 Vulnerability Analysis and Component Importance

Network vulnerability analysis emerged from the network reliability literature, which is often interested in the probability of a desired network performance (Boesch 2009) or the consequences of the failure of a network component regardless of the probability of failure (Taylor and Susilawati 2012, Ramirez-Marquez et al. 2016). This second perspective enables the calculation of component importance measures, a long-studied area in reliability engineering (Kuo and Zhu 2012), wherein network components that impact the performance of the network are identified.

Step 4 develops scenario-specific component importance measures based on vulnerability. The consideration of the economic impacts of a disruption of transportation network components enhances the literature on transportation network vulnerability, which have traditionally focused on flow or topological aspects of the network (e.g., connectivity and accessibility) as metrics for network performance (Reggiani et al. 2015, Mattsson and Jenelius 2015, Sun et al. 2017). As such, when we define our new importance measure, we consider the ultimate role of a freight transportation network as a facilitator of economic productivity. Such impact is calculated for different disruptive scenarios, e^p, where p represents the component removed from the network (as displayed in Figure 2.1). As a result, this work advances the study of network vulnerability from the perspective of network performance in terms of commodity-driven multi-industry impact rather than graph theoretic or flow importance measures. Malfunction of a freight transportation network serving a regional economy -- comprised of interdependent industries -- causes failure in the form of a delayed shipment of commodities at supply nodes and/or unmet demands at demand nodes. Here, the interdependent effect of the failure in multiple industries is captured by the IIM as described in Section 2.2.3. And finally, vulnerability is defined as the magnitude of this failure in terms of multi-industry economic impact, given the occurrence of a particular disruptive event, e^p. Note, of course, that network vulnerability is highly dependent upon the type and extent of e^p, which assumes complete removal of component p (though a proportional reduction could also be explored).

Two vulnerability measures, stated in Eqs. (2.13) and (2.14), are proposed. For network topology G, fixed demand/supply vector $\mathbf{b}$, and disrupted (removed) component p, vulnerability is measured as the relative network efficiency, or the multi-industry economic loss $Q(G-p,\mathbf{b})$, after p is removed from the network, G. $Q_{\max}$ is the maximum multi-industry loss caused by a shutdown in the entire network (i.e., a removal of all nodes). As such, the vulnerability measure in Eq. (2.13) quantifies the proportional economy-wide impact of a loss of component p relative to a loss in all components. This measure lies on (0,1), where 0 means that losing component p has no effect on the total economy and 1 means that the loss of component p is as disruptive as having a shutdown of the entire network.

$$\eta_p(G,\mathbf{b}) = \frac{Q(G-p,\mathbf{b})}{Q_{\max}} \tag{2.13}$$

Eq. (2.14) similarly provides the economic vulnerability experienced by a particular industry k due to lost component p, providing an industry-by-industry perspective to the importance of vulnerable transportation network elements. $Q_{\max}^{k}$ is the maximum loss in a particular industry k caused by a shutdown in the entire network, capturing indirect economic loss effect on each industry based on the IIM.

$$\eta_p^k(G,\boldsymbol{b}) = \frac{Q_k(G-p,\boldsymbol{b})}{Q_{max}^k} \tag{2.14}$$

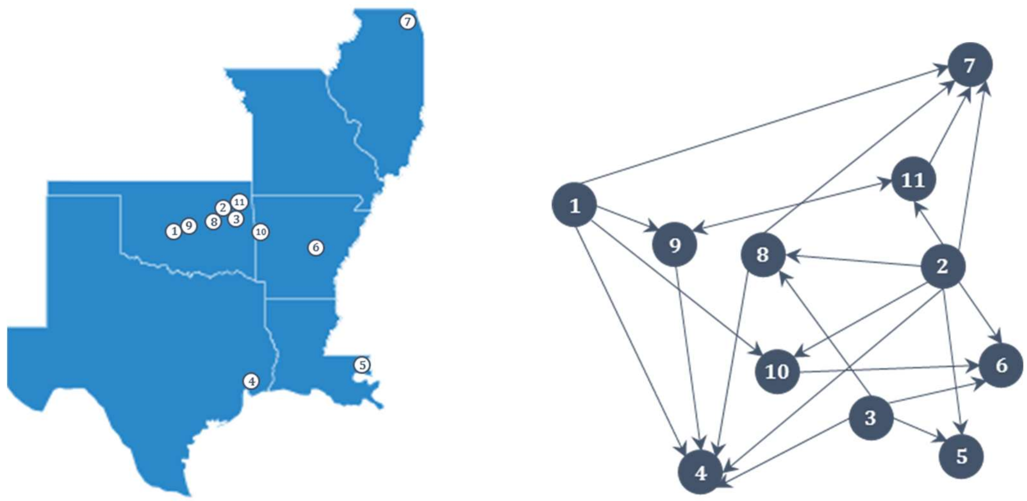
Thus, Eqs. (2.13) and (2.14) provide economy-wide and industry-specific vulnerability measures for the disruption of component p in the multi-modal transportation network. Naturally, certain industries may be more impacted by certain network components than others, which is an important consideration (e.g., a particular industry may be more critical to a state or regional economy than another).

2.3 Illustrative Example

The proposed transportation network vulnerability analysis methodology and component importance measures, found as a result of the four-step process in Section 2.2, is illustrated with a case study based on a portion of a multi-modal freight transportation network within the state of Oklahoma and surrounding states whose industries trade with Oklahoma industries. Oklahoma plays a strong role in the transport of goods via a multi-modal transportation network consisting of three important interstate highways, as well as railways and inland waterways that connect to the Mississippi River Navigation System via two ports.

2.3.1 Baseline Network Flow, Illustrated

Figure 2.3 highlights a supply-demand network in which supply nodes are all within the state of Oklahoma: the three important business economic areas of Oklahoma City (node 1), the Port of Catoosa in Tulsa (node 2), and the Port of Muskogee (node 3) (Ingalls et al. 2002). Demand nodes consist of states external to Oklahoma that are the most important states to interact with Oklahoma industries: Texas, Louisiana, Arkansas, and Illinois. The effects of a disruption within the network on exporting industries within the state are sought, as are the consequences in the entire Oklahoma economy, hence the four importing states are considered as four combined demand nodes connecting to Oklahoma's multi-modal freight transportation network.



(a) (b)

Figure 2.3. Representations of (a) spatial location of multi-modal nodes in Oklahoma and surrounding states, and (b) the connected transportation network.

The nodes of the network are discussed in brief in Table 2.1 The Oklahoma City business economic area is connected to the north-south corridor through I-35 and east-west corridor through I-40 and I-44. In addition to the truck way facilities, Burlington Northern Santa Fe (BNSF) railroad has an intermodal rail-truck facility in Oklahoma City near the junction of I-35 and I-40. The Port of Catoosa, the largest inland port in the United States in terms of area, is located near the city of Tulsa, adjacent to I-44, US 169, and rail lines. Industries listed in Table 2.2 are almost the port's largest exporters in terms of commodity flows. The Port of Muskogee is connected to the freight transportation network through Highway 165 and a rail marshalling yard. Supply nodes in Figure 2.3 include Oklahoma City (node 1), the Port of Catoosa (node 2), and the Port of Muskogee (node 3). Demand nodes include Texas city, TX (node 4), New Orleans, LA (node 5), Little Rock, AR (node 6), and Chicago, IL (node 7). Node 8 represents the intermodal terminal that facilitates the movement of commodities from industries in the industrial park of Port of Catoosa to their out-of-state customers using railroad company, BNSF. Links (1,7) and (1,4) are part of the North America railroad which connects Oklahoma City, OK, with Chicago, IL, and with Texas City, TX, respectively. The Port of Catoosa is connected to the North America railroad through a local railroad represented by link (2,8). Links (2,5), (2,4), (2,6), and (2,7) are part of the inland waterway network navigated by McClellan–Kerr Arkansas River Navigation System and connect Port of Catoosa with the Port of New Orleans, the Port of Texas City, the Port of Little Rock, and the Port of Chicago, respectively. The Port of Muskogee is connected to the Port of Little Rock, the Port of Texas City, and the Port of New Orleans through the same inland waterway network represented by links (3,6), (3,4), and (3,5), respectively, and it is linked to the North America railroad through a local railroad depicted with link (3,8). Node 9 is an intermediate node that connects the Oklahoma City business economic area to the U.S. interstate highways to the north and south through I-35 and to the east through I-44. Node 10 is Fort Smith, AR which is a connecting point on I-40 to link Oklahoma City and Tulsa, OK to Little Rock, AR. Node 11 represents an intermediate node that connects the Port of Catoosa industrial park to interstate highway I-44, link (9,4) connects Oklahoma City to Texas City, TX, using interstate highways I-35 and I-45, and link (9,11) is part of interstate highway I-44 which connects Oklahoma City to Tulsa.

Table 2.1 Spatial location of multi-modal nodes in Oklahoma and surrounding states.

Component	Description
Node 1	Oklahoma City, a supply node for multiple industries
Node 2	Port of Catoosa, a supply node for multiple industries
Node 3	Port of Muskogee, a supply node for multiple industries
Node 4	Port of Texas City, a demand node for multiple industries
Node 5	Port of New Orleans, a demand node for multiple industries
Node 6	Port of Little Rock, a demand node for multiple industries
Node 7	Port of Chicago, a demand node for multiple industries
Node 8	Intermodal terminal, Tulsa, OK
Node 9	Transshipment node that connects the Oklahoma City, OK, business economic area to the north and south through I-35 and to the east through I-44
Node 10	Transshipment node in Fort Smith, AR, that is a connecting point on I-40 to link Oklahoma City and Tulsa, OK to Little Rock, AR
Node 11	Transshipment node that connects the Tulsa Port of Catoosa industrial park to I-44
Link (1,7)	Part of the North America railroad that connects Oklahoma City, OK with Chicago, IL
Link (8,7) and Link (8,4)	Part of the North America railroad which connects Tulsa, OK, with Chicago, IL and Texas City, TX, respectively
Link (2,8)	A local railroad connecting Port of Catoosa to the North America railroad
Link (1,4)	Part of the North America railroad that connects Oklahoma City, OK with Texas City, TX
Links (2,5), (2,4), (2,6), and (2,7)	Part of the inland waterway network navigated by McClellan–Kerr Arkansas River Navigation System and connect Port of Catoosa with the Port of New Orleans, the Port of Texas City, the Port of Little Rock, and the Port of Chicago, respectively
Links (3,6), (3,4), and (3,5)	Part of the inland waterway network navigated by McClellan–Kerr Arkansas River Navigation System and connect the Port of Muskogee to the Port of Little Rock, the Port of Texas City, and the Port of New Orleans, respectively
Link (9,4)	The roadway that connects Oklahoma City to Texas City, TX using interstate highways I-35 and I-45
Link (9,11)	Part of interstate highway I-44 that connects Oklahoma City to Tulsa.

In total, there are 62 industries operating in Oklahoma as identified by NAICS, suggesting that the $\mathbf{A}^{\star}$ matrix regionalized for Oklahoma is 62×62. In the proposed supply-demand network, six industries, listed in Table 2.2, are considered to be industries that primarily export commodities to out-of-state customers according to high trade figures (Bureau of Transportation Statistics 2010a). In the developed illustrative MCNF example, each commodity belongs to an industry as defined by NAICS economic sectors, and each node within the network is considered to be either a supplier or a customer of a particular commodity.

Table 2.2. Names and NAICS codes for main industries using the network.

Industry name	NAICS code
Food and beverage and tobacco products	311
Petroleum and coal products	324
Chemical products	325
Nonmetallic mineral products	327
Machinery	333
Miscellaneous manufacturing	339

Table 2.3 lists the combined estimated annual supply and demand in tons for the associated industries and states, compiled from different databases (US Army Corps of Engineers 2013, Tulsa Port of Catoosa 2013, Bureau of Transportation Statistics 2010a,b, Port of Muskogee 2013, Bureau of Economic Analysis 2010).

Table 2.3. Combined annual demands/supplies at supply/demand nodes connecting through the network (in thousand tons).

	Food and beverage	Petroleum and coal	Chemical products	Nonmetallic mineral	Machinery mfg.	Misc. mfg.
Supply nodes in OK						
Oklahoma City	4351	0	3606	2198	285	1419
Port of Catoosa	603	5459	3416	303	30	5
Port of Muskogee	0	408	0	383	0	361
Demand nodes outside of OK						
Texas City, TX	1167	3804	2448	0	310	362
New Orleans, LA	604	221	0	0	3	0
Little Rock, AR	3183	1842	4574	492	2	654
Chicago, IL	0	0	0	2392	0	769

Baseline network flow in the supply-demand network is calculated with model M1, where the cost vector is computed based on the transportation mode and the mileage of the distances between nodes. The cost per ton-mile for a barge is estimated at \$0.97, compared to \$2.53 for rail, and \$5.35 for trucking (Arkansas Waterway Commissions 2014). The capacity of each link, shown in Table 2.4, representing the availability of transportation facilities, is estimated from historical data as a shared constraint for all commodities flowing on the link (ODOT 2013). The baseline flow resulted in no remaining commodities at supply nodes and no unsatisfied demand at demand nodes, suggesting that supply nodes send out all the commodities and demand nodes satisfy all their demands. Based on Table 2.3, the total supply of commodity k is assumed to be equal to the total demand of the same commodity within the entire supply-demand network as depicted in Figure 2.3.

Table 2.4. Link capacities among the origin/destination nodes in the illustrative network (in thousand tons) (ODOT 2013).

Nodes	4	5	6	7	8	9	10	11
1	2800			2900		1700	6200	
2	180	650	750	500	3400		3700	1350
3	355	185	3010		290			
8	3800			300				
9	1800							1700
10			12000					
11				1600		2000		

2.3.2 Network Disruption, Illustrated

Considering a disruptive scenario as the removal of a particular network component, the supply-demand network might experience a failure in satisfying demands in the interrupted network. The network components that were considered for disruption include: (i) three transshipment nodes within the state of Oklahoma, which have a vital role in connecting segments of high volume-freight-traffic interstate highways, (ii) some segments of the North America Railroad, (iii) a local railroad which connects industrial parks to the North America Railroad, and (iv) parts of waterway system (described in Table 2.1). Discussed previously in Section 2.2.2, a decision maker would likely desire to reroute commodities to take advantage of the remaining capacity of the residual network, as shown in model M2, by maximizing the flow to meet as much demand as possible given the interrupted network. Failure in the form of undelivered commodities remaining with the suppliers, or unsatisfied demand at demand nodes, represented by S_i^k, affect industry output and inoperability propagates through many of the interconnected industries. In the illustrative example, all the supply nodes are within the state of Oklahoma and the four demand nodes are located outside of Oklahoma. Table 2.5 reports $\sum_{i\in(N_+\cap N_k)} S_i^k$, the sum of the slack (remaining supply) by industry type at the supply nodes when different network components are disrupted.

Table 2.5. Commodities remaining at suppliers with the removal of network components (in thousand tons).

Removed component	Food and beverage	Petroleum and coal	Chemical products	Nonmetallic mineral	Machinery mfg.	Misc. mfg.
Node 9	291	0	803	0	25	2
Node 8	478	2508	623	0	0	7
Node 11	34	143	1067	0	25	7
Link (1,7)	290	0	0	2000	0	770
Link	189	108	823	0	0	0
Link (2,5)	504	37	0	0	28	0
Link (8,4)	367	2108	923	0	0	7
Link (2,8)	189	2308	823	0	0	5
Link (2,4)	0	105	0	0	0	0
Link (3,8)	0	0	0	210	5	0
Link (8,7)	0	0	0	251	0	0

2.3.3 Multi-industry Impact, Illustrated

In the case of any disruption within the network resulting in the loss of exports, there is a demand perturbation in the industries using the network, as calculated in Eq. (2.13). Assuming the only losses in the state economy are due to the loss of exports, the interdependent cascade of the demand perturbations causes losses to all the other state industries, as captured in Q. It is further assumed that industries not using the transportation network have zero demand perturbations, though could suffer from interdependent inoperability.

As network component importance rankings are ultimately calculated on a relative basis, inoperability is calculated in terms of annual impact, as it is assumed that annual industry production accumulates consistently across the year (i.e., neither production nor interdependency relationships vary day-to-day, week-to-week, month-to-month). A smaller time horizon could be considered as a proportion of a year if a particular disruptive event is modeled (e.g., a two-week closure of port facilities (Pant et al. 2011)).

Using the remaining commodities left at supply nodes, shown in Table 2.5, demand perturbations were calculated with Eq. (2.13). In the example, the industries in Oklahoma experience difficulties in exporting commodities, individually for each of the 11 disrupted network components. The resulting industry inoperability, q^k, for each disrupted component is found, as shown in Table 2.6 and plotted in Figure 2.4. Results show that most industries are vulnerable to disruptions that affect the functionality of either rail transportation or interstate highways but less susceptible to disruptions to the inland waterway which has a smaller share (less than 5% (ODOT 2013)) in outbound freight movement in Oklahoma. As such, perhaps the external capacity in rail and truck freight transport suggest that they could serve as alternative transportation modes during a disruption, though more costly. A disruption that affects the functionality of the intermodal terminals would cause the most significant drop in the productivity of most industries. Examples of this include (i) node 8, which facilitates trade between industries located in the business economic area in Port of Catoosa, OK with their customers in Chicago, IL and Texas City, TX through the North America railroad, and (ii) nodes 9 and 11, important transshipment nodes that connect the three important business economic areas within the state of Oklahoma to their customers through interstate highways.

From a single industry point of view, it is shown that the productivity of the *Petroleum and coal* (324) industry is mostly vulnerable to its accessibility to the North America railroad through the intermodal terminal (node 8) in Tulsa, OK. In general, most disruption scenarios may affect the productivity of the *Chemical products* (325) industry, either by a local disruption that interrupts the access of the business economic area at the Port of Catoosa through a local railroad (e.g., link (2,8) to the intermodal terminal at node 8) or a state-wide disruption that affects Oklahoma's major trucking corridors (e.g., interstate highways I-35, I-44, and I-40). Also shown is that parts of the transportation network that are less important for most industries may be quite important to the productivity of a particular industry (e.g., the *Nonmetallic and mineral products* (327) industry is influenced by the malfunction of the local railroad which connects the Port of Muskogee to the North America railroad (link (3,8)) though all the other five industries are much less vulnerable to this link). Understanding these inoperability-related vulnerabilities could motivate further studies to guide investments in alternative transportation modes. The inoperability values in Table 2.6 may appear to be negligible at first, but these numbers are significant when linked to the concept of failure probability in the reliability or quality engineering literature (i.e., the maximum allowable failure probability for a six-sigma compliant system is 3.4E-06).

Table 2.6. Interdependent industry inoperability resulting from network component removal.

Removed component	Food and beverage	Petroleum and coal	Chemical products	Nonmetallic mineral	Machinery mfg.	Misc. mfg.
Node 9	2.98E-04	7.15E-06	4.37E-04	1.21E-05	1.81E-04	2.64E-05
Node 8	4.93E-04	1.11E-03	4.25E-04	4.03E-05	1.82E-05	9.44E-05
Node 11	3.61E-05	6.83E-05	5.71E-04	8.27E-06	1.80E-04	2.37E-05
Link (1,7)	3.02E-04	1.11E-05	2.86E-05	9.12E-04	7.71E-06	5.56E-04
Link (9,11)	1.94E-04	5.20E-05	4.43E-04	6.54E-06	2.37E-06	1.42E-05
Link (2,5)	5.16E-04	2.28E-05	2.43E-05	1.69E-05	2.05E-04	3.36E-05
Link (8,4)	3.80E-04	9.33E-04	5.66E-04	3.34E-05	1.53E-05	8.01E-05
Link (2,8)	1.98E-04	1.02E-03	5.14E-04	3.15E-05	1.53E-05	7.61E-05
Link (2,4)	1.61E-07	4.63E-05	3.39E-06	1.20E-06	6.19E-07	2.79E-06
Link (3,8)	1.41E-07	7.11E-07	2.15E-06	1.06E-04	3.80E-05	2.84E-06
Link (8,7)	7.10E-08	4.90E-07	1.36E-06	1.26E-04	2.30E-07	9.62E-07

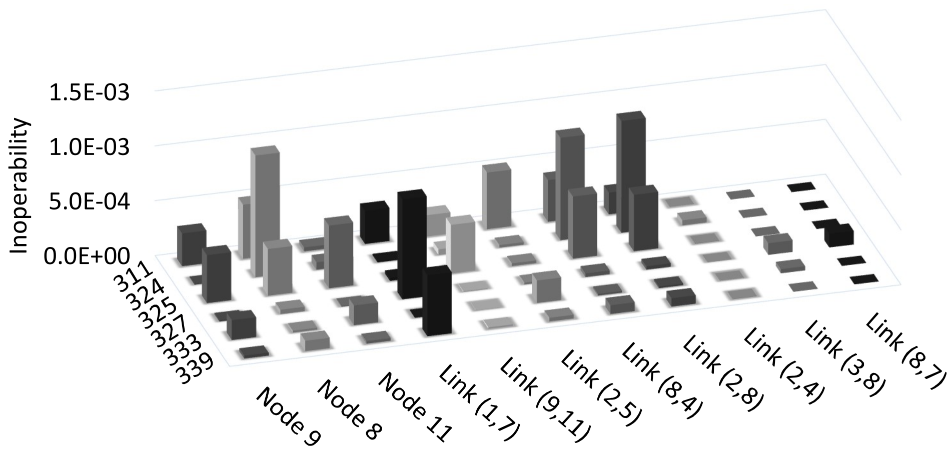


Figure 2.4. Economic inoperability across six most important industries within the state of Oklahoma.

In addition to inoperability, the complementary perspective of economic losses in Table 2.7 can supplement the analysis. The *Petroleum and coal products* (324) industry is a high dollar industry in Oklahoma, and this industry would be significantly impacted by a disruption that affects the functionality of rail transportation (e.g., a local railroad such as link (2,8), part of the level-one railroad that connects Oklahoma to the North America railroad such as link (8,4), or intermodal terminal facilities such as node 8. A second prominent industry is the *Food, beverage, and tobacco products* (311) industry, and several transportation components contribute to the dollar volume of production in this industry, especially a part of the inland waterway network that connects Port of Catoosa with the Port of New Orleans, LA (link (2,5)), and part of the North America railroad that connects Tulsa, OK with Texas City, TX (link (8,4)). In fact, the intermodal terminal (node 8) which facilitates freight transport at the Port of Catoosa is a prominent component in the dollar volume of several exporting industries in Oklahoma. In general, rail transportation and major trucking corridors have a high impact on the economy of most industries, though less important components (e.g., part of the inland waterway such as links (2,4) or (2,5)) may still have a large impact on a particular industry (e.g., *Miscellaneous manufacturing* (339) and *Petroleum and coal products* (324) by millions of dollars).

Table 2.7. Economic losses (in 100 million USD) across the six most important industries within the state of Oklahoma.

Removed component	Food and beverage	Petroleum and coal	Chemical products	Nonmetallic mineral	Machinery mfg.	Misc. mfg.
Node 9	1.627	0.090	0.594	0.025	1.308	0.267
Node 8	2.688	13.974	0.578	0.082	0.132	0.954
Node 11	0.197	0.860	0.777	0.017	1.304	0.240
Link (1,7)	1.647	0.140	0.039	1.854	0.056	5.622
Link (9,11)	1.059	0.655	0.602	0.013	0.017	0.143
Link (2,5)	2.813	0.287	0.033	0.034	1.484	0.340
Link (8,4)	2.072	11.757	0.769	0.068	0.111	0.810
Link (2,8)	1.079	12.837	0.698	0.064	0.111	0.769
Link (2,4)	0.001	0.583	0.005	0.002	0.004	0.028
Link (3,8)	0.001	0.009	0.003	0.216	0.275	0.029
Link (8,7)	0.001	0.001	0.002	0.256	0.002	0.010

2.3.4 Vulnerability Analysis and Component Importance, Illustrated

The component importance measures, quantifying the proportional economy-wide impact of a loss of component p relative to a loss of the whole network, are calculated with Eq. (2.13) and are depicted in Figure 2.5. This measure lies on (0,1), where $\eta_p = 0$ means that the removal of component p doesn't affect the whole economy, and $\eta_p = 1$ means that the particular component removal shut downs the whole economy. As shown in Figure 2.5, the most important components relate to the rail transportation and major trucking corridors. A main component of the rail freight transport, node 8 is the intermodal terminal facilitates the movement of commodities in the industrial park of

Port of Catoosa to out-of-state customers and is the most important component in the analyzed transportation network. This facility is followed by link (8,4), a portion of railroad that connects Oklahoma to Texas City, TX, link (2,8), a local railroad that connects the Port of Catoosa to the North America railroad intermodal terminal, and link (1,7), a portion of railroad that connects Oklahoma City, OK to Chicago, IL. This suggests a further attention to the functionality of the facilities of the most important components within the network to avoid any malfunction, or in the case of any disaster which deactivates multiple components of the network, there should be priorities to recover the most important components. The framework proposed here could be used to evaluate alternative transportation modes for shipping commodities after a disruption or to guide planning for transportation investments to reduce vulnerability, and thus multi-industry impacts.

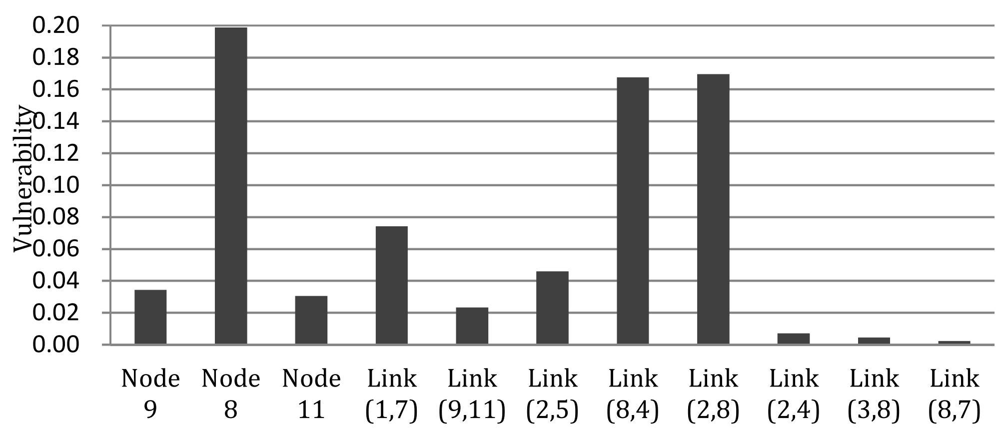


Figure 2.5. Network component importance measures across the Oklahoma economy using $\boldsymbol{\eta_p(G, \mathbf{b})}$.

Figure 2.6 emphasizes component importance to individual industries, quantifying the proportional impact of a loss of component p on a particular industry relative to the impact of a loss in all components on that industry, as calculated with Eq. (2.14). This measure lies on (0,1), where ${\eta_p}^k = 0$ means that the removal of component p does not affect industry k, while ${\eta_p}^k = 1$ suggests that the particular component removal completely shuts down industry *k*. As it is shown in Figure 2.6, any failure that results in disconnection of link (2,5), the inland waterway connecting the Port of Catoosa to the Port of New Orleans, would have the largest impact on *Food, beverages, and tobacco products* (311) relative to other industries. The intermodal terminal (node 8), which connects the Port of Catoosa to its out-of-state customers through the North America railroad, has the largest impact on *Petroleum and coal products* (324). It also demonstrates that the malfunction of local railroads (e.g., link (2,8)) may have a high impact on the productivity of *Petroleum and coal products* (324). In addition, the *Nonmetallic and mineral products* (327) industry, primarily located in the Oklahoma City business economic area, is highly vulnerable to the functionality of the part of the North America railroad that connects Oklahoma City, OK with Chicago, IL. Note that some components are important from the perspective of a particular industry though perhaps not the entire economy, such as link (1,7), which suggests lower priority in Figure 2.5 but is quite impactful for the *Nonmetallic and minerals products* (327) industry. Figure 2.5 also suggests that the *Petroleum and coal products* (324) industry can be impacted by the disruption of several network components, more so than any other industry.

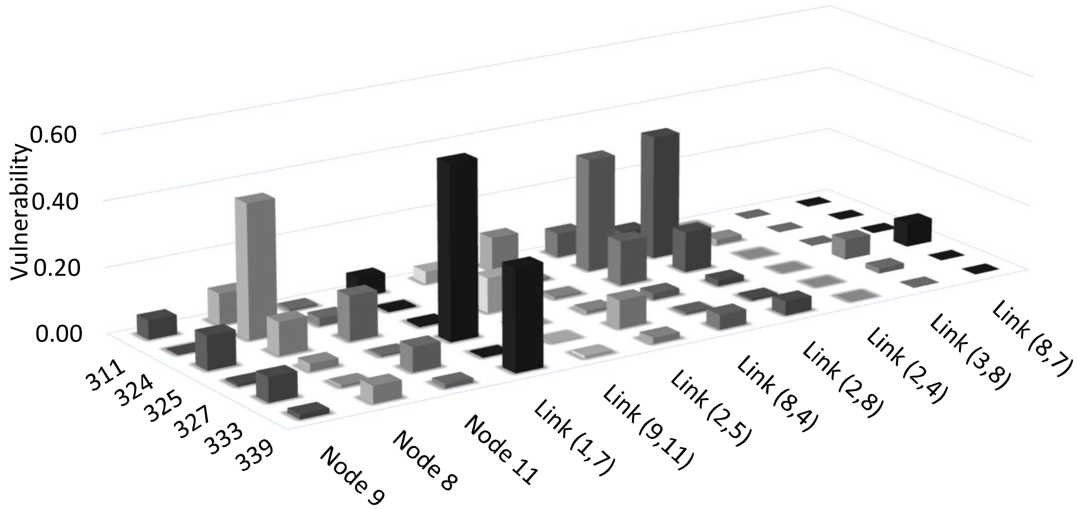


Figure 2.6. Network component importance measures focusing on particular Oklahoma industries using $\boldsymbol{\eta_p^k}(\boldsymbol{G}, \mathbf{b})$.

2.4 Concluding Remarks

Transportation network vulnerability studies have largely attempted to quantify the reduction in system functionality, following a disruption, as (i) topological properties of the network, and (ii) flow importance measures. These structural and flow-related measures ignore a larger role that the transportation network plays in facilitating economic productivity. This work offers a broader perspective on freight transportation network vulnerability analysis with a means to measure importance of network components considering economic impacts of degradation of transportation network. In particular, this study considers a multi-modal freight network consisting of highway, railway, and waterway transportation, and implements the proposed vulnerability analysis framework to understand and rank the criticality of multi-modal transportation nodes and links.

A four-step approach (i) calculates baseline (undisrupted) multi-commodity flow according to minimum cost, (ii) measures slack at supply and demand nodes, in the form of undelivered supply and unmet demand, when individual components are removed (one-at-a-time) from the network according to a maximum flow perspective, (iii) relates slack in the network to perturbations and inoperability among interdependent industries relying on commodities flowing along the network, and (iv) quantifies the importance of each component from industry-specific and overall regional economy perspectives. The primary contribution of this approach is the integration of the multi-commodity network flow representation of the multi-modal transportation network with the interdependent, multi-industry economic model and a framework to measure a transportation network component importance considering its multi-industry impact.

This approach is illustrated with a stylized case study of a multi-modal transportation network in the state of Oklahoma, where supply nodes are located within the state and demand nodes are located outside of the state. Results of the case study suggest that the *Petroleum and coal products* industry is particularly susceptible to disruptions in several components, and certain components can impact multiple industries. Also, analysis shows that the economy of the state and most industries are primarily vulnerable to the malfunction of the parts of the railway that connect the state to the North America railroad and major trucking corridors including interstate highways I-35, I-44, and I-40. While the application pursued in this study focused primarily on the state of Oklahoma, the base model can be applied to other freight transportation networks to identify the critical nodes/links that can instigate the largest vulnerability across interdependent sectors that uniquely vary from region to region. Hence, the proposed model and its future applications could provide significant value to homeland security preparedness planning.

Furthermore, the vulnerability analysis perspective proposed in this study can be implemented to highlight priorities in maintaining certain network components (to reduce common-cause failure), or in rerouting of commodity flows after a disruption. There also exists an opportunity to extend the base approach discussed in this work to analyze network completion strategies where capacity enhancement (e.g., link capacity) and additional transportation facilities (e.g., added links/nodes) could harden the network around the most vulnerable components. Further, longer term transportation infrastructure design plans could be informed by this kind of analysis.

CHAPTER 3

INVESTING FOR ABSORPTIVE CAPACITY IN INTERDEPENDENT INFRASTRUCTURE AND INDUSTRY SECTORS

3.1 Introduction

Freight transportation infrastructure, including ports, intermodal stations, interstate highways, and railways as basic structures and facilities, enable commodity flows and facilitate the productivity of industries. In the past decades, numerous disruptive events, whether natural hazards, human-made events or common failures, have threatened the operation of multiple modes of this infrastructure system and consequently adversely impacted economic productivity. A few examples include flooding of the Mississippi and Missouri rivers in 1993, where several railroads experienced delays and cancelations (Haefner et al. 1996), Hurricane Katrina that caused damage to the American highway system in Louisiana, Mississippi, and Alabama in 2005 (Shen and Aydin 2014), and Hurricane Sandy, as a multi-storm which hit the East Coast of the US in 2012, that caused all port terminal facilities and the harbor closure at the Port of New York/New Jersey area (Fialkoff et al. 2017). A local disruption (i.e., port closure) can have effects that propagate through the system of interdependent infrastructure and industry sectors resulting in major reductions in economic efficiency regionally or nation-wide (Pant et al. 2011, Arnold et al. 2006). A protective approach could include "hardening" key industries to lessen the shocks from disruptive events (DHS 2013). This work provides an approach to measure such hardening in terms of the effectiveness of investing in resilience from the perspective of a central decision maker across several interdependent industries.

This work focuses on reducing vulnerability via absorptive capacity. The idea of absorptive capacity has also been referred to as *static resilience*, or "the ability of the system to maintain functionality when shocked" (Rose 2007). Mathematically, static resilience is measured in terms of the difference between the maximum potential drop in system performance and the estimated performance drop (Rose 2004). That is, no notion of recovery is considered, only the ability to withstand the initial disruption. This is depicted graphically in Figure 3.1 and mathematically in Eq. (3.1), where $\%\Delta DY$ represents the actual percentage change in the performance of the system following a disruptive event and $\%\Delta DY^{max}$ represents the maximum percentage change given the worst-case level of performance (Rose 2009). This quantitative approach is used in this study to define a performance measure for the system's ability to absorb shocks ($\%\Delta DY^{max} - \%\Delta D$) from disruptive events, though we prefer the term *absorptive capacity* rather than static resilience.

While Figure 3.1, from Pant et al. (2014), represents changes in system performance in a general sense, Rose (2009) provides a more specific application, where $\%\Delta DY$ and $\%\Delta DY^{max}$ refer to changes in total output produced in an economy of interconnected industry sectors. In this sense, these measures are analogous to the concept of inoperability, a well-studied topic in the literature of interdependent industries and infrastructures (Santos and Haimes 2004, Barker and Haimes 2009, Barker and Santos 2010a,b). Inoperability, q, quantifies the proportional extent to which a system (e.g., economic system) is not functioning in an as-planned manner, thereby providing a metric to describe the behavior of a system regardless of the measure describing its proper function (e.g., flow capacity, connectivity, production output).

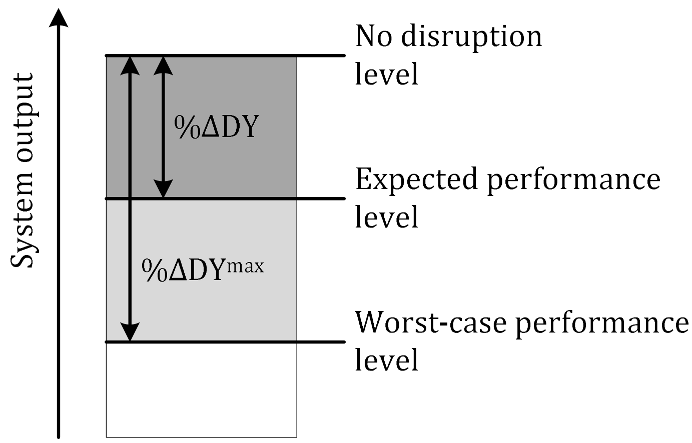


Figure 3.1. The performance components of static resilience (Pant et al. 2014).

$$absorbtive\ capacity\ (static\ economic\ resilience) = \frac{\%\Delta DY^{max} - \%\Delta DY}{\%\Delta DY^{max}} \tag{3.1}$$

This chapter seeks to answer: how should limited resources can be allocated to harden individual industries effectively to enhance absorptive capacity with total economic impacts in mind? These economic impacts are realized due to freight disruptions. Freight transportation infrastructure disruptions lead not only to physical damage, but also to an interruption of economic productivity across multiple industries due to infrastructure inoperability (Ham et al. 2005, Park et al. 2011). Arnold et al. (2006) analyzed economic impacts of disruptions in container traffic in the ports of Los Angeles and Long Beach, California. Pant et al. (2011), using the Inoperability Input-Output

Model (IIM) (Santos and Haimes 2004), showed how a local disruption in the Port of Catoosa in Tulsa, OK, would affect multiple industry sectors within the state of Oklahoma and neighboring states that trade with Oklahoma. Understanding the absorptive capacities of affected industries could inform preparedness planning against impacts. In particular, preparedness plans could enhance the ability of the industry sectors to absorb shocks from the disruptive events and lessen the maximum economic inoperability that the series of interdependent industries would experience.

This chapter establishes inoperability, through the IIM, as a means to measure absorptive capacity in interdependent industries. IIM is a data-driven model that contains uncertainties due to inherent linearity or proportionality assumptions and/or inexactness in data collection, allocation, and integration (Pant et al. 2011). This research addresses (i) defining a measure of absorptive capacity to invest for resilience in an interdependent economic system, and (ii) planning for absorptive capacity under uncertainty, while (iii) addressing some of the uncertainties of the model.

3.2 Methodological Background

The IIM is an extension of the economic input-output model (Leontief 1986), for which Wassily Leontief won a Nobel prize. The input-output model has been widely accepted as a useful model for analyzing the interdependent connections among industries. In a system of n interacting industries under a static equilibrium, the total output of the i^{th} industry is distributed to all other industries and also satisfies external demand. This equilibrium condition is described with $x_i = \sum_{j=1}^{n} z_{ij} + c_i$, where x_i is the output, c_i is the external demand for industry i, and z_{ij} describes the flow of commodities output from industry i and used as input to production in industry j. The flow of commodities z_{ij} is assumed to be proportional to the output of industry j, expressed as $z_{ij} = a_{ij}x_j$. The common form of the Leontief input-output model is expressed in Eq. (2.1) where **x** is an $n\times1$ vector of industry production outputs, **A** is an $n\times n$ industry-by-industry matrix of interdependency coefficients, and **c** is a $n\times1$ vector of final demands. The model shows that total production is made up to satisfy industry-to-industry intermediate production (**Ax**) and final demands (**c**).

Instead of describing the connections between the interdependent industry sectors in terms of commodity flow in monetary units (e.g., dollars), the IIM illustrates how normalized production losses propagate through all interconnected industries. The IIM gives us inoperability as an alternative metric for examining the effects of a disruption. The IIM is provided in Eq. (2.3) (Santos and Haimes 2004), which describes the relationships among n infrastructure and industry sectors, resulting in matrices of size $n\times n$ and vectors of length n.

As is evident from Eq. (2.3) the IIM, like the economic input-output model of Eq. (2.1), is a demand-driven model. Specifically in the IIM disruptions are translated to demand perturbations giving direct economic losses, following which the indirect economic losses can be estimated through Eq. (2.3). Total economic losses, the combination of direct and indirect losses, can be calculated by multiplying each industry's production level by its inoperability level: for industry i, $Q_i = x_i q_i$, or for the entire economy of industries, $Q = \mathbf{x}^T\mathbf{q}$. As such, planning decisions can be made with respect to inoperability or economic impact at the sector level, or with respect to economic impact at the multi-sector level.

While the input-output model, and its inoperability-based extension, may appear to be overly simple in its linear construction, the validity of the model is attested for by the vast amount of literature in which it is used. In addition, there are detailed data sets available to support analysis with the model, including the commodity flow data published annually by the U.S. Bureau of Economic Analysis (BEA) and many other countries worldwide.

3.3 Absorptive Capacity Measures and Planning Framework

A disruption within a freight transportation infrastructure affects industries that rely on the operation of these facilities to move commodities. The disruption propagates through the interdependent system and causes regional and national economic inoperability. As discussed in Section 3.2, the interdependent economic impacts of the disruption is calculated using the IIM, and subsequently in Section 3.1, a measure of absorptive capacity is defined based on the concept of static economic resilience (Rose 2009, Pant et al. 2014). We propose an optimization framework to devise a strategy to allocate limited budget to industry sectors to enhance the absorptive capacity. Epistemic data uncertainty in the IIM is considered and decision making under uncertainty is discussed.

3.3.1 Defining Absorptive Capacity with Inoperability

Suggested previously, the percentage change in the performance of a system, $\%\Delta DY$, is analogous to the measure of inoperability, q, which represents the proportional extent to which a system is not properly functioning. If we define $q_{\max}$ as the maximum possible inoperability that could be experienced after a disruptive event, a measure of absorptive capacity is provided in Eq. (3.2). Absorptive capacity of sector i is referred to with convention $Я_i^S$, adopting the *Я* notation of Whitson and Ramirez-Marquez (2009) as *R* often refers to *reliability*.

$$Я_i^S = \frac{q_{i,max} - q_i}{q_{i,max}} \tag{3.2}$$

Using the convention $\mathbf{D}^\star = \left[d_{ij}^\star\right] = [\mathbf{I} - \mathbf{A}^\star]^{-1}$, Eq. (2.2) can be written as $\mathbf{q} = \mathbf{D}^\star \mathbf{c}^\star$. As such, inoperability in sector *i* can be represented with Eq. (3.3).

$$q_i = \sum_{j=1}^{n} d_{ij}^\star c_j^\star \tag{3.3}$$

As shown in Eq. (3.4), using the demand-driven paradigm, the absorptive capacity for sector *i* can be written as a function of maximum and expected demand perturbation levels, $c_{j,\max}^\star$ and $c_j^\star$, respectively. $Я_i^S$ measures the proportional "savings" in inoperability when a priori planning can stave off the worst-case inoperability outcome in favor of reduced inoperability.

$$Я_i^S = \frac{\sum_{j=1}^{n} d_{ij}^\star c_{j,max}^\star - \sum_{j=1}^{n} d_{ij}^\star c_j^\star}{\sum_{j=1}^{n} d_{ij}^\star c_{j,max}^\star} = \frac{\sum_{j=1}^{n} d_{ij}^\star \left(c_{j,max}^\star - c_j^\star\right)}{\sum_{j=1}^{n} d_{ij}^\star c_{j,max}^\star} \tag{3.4}$$

To capture absorptive capacity across the entire set of interdependent infrastructure and industry sectors, a more appropriate economic resilience metric would account for the widespread ability of sectors to collectively maintain operability following a disruptive event. As such, individual sector inoperability is multiplied by sector output, in dollar terms. In summation form, this is represented with $Q_i = \sum_{j=1}^{n} x_i d_{ij}^\star c_j^\star$. The resulting absorptive capacity metric is provided in Eq. (3.5).

$$Я^S_{total} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i d^\star_{ij} c^\star_{j,max} - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i d^\star_{ij} c^\star_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i d^\star_{ij} c^\star_{j,max}}$$
$$= \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i d^\star_{ij}\left(c^\star_{j,max} - c^\star_j\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i d^\star_{ij} c^\star_{j,max}} \tag{3.5}$$

3.3.2 Planning for Absorptive Capacity

Resource allocation requires developing strategies that reduce demand perturbations effectively, thus leading to economic resilience. This demand-driven approach is consistent with the idea that static resilience (absorptive capacity) is a consequence of efficient utilization of resources and not system repair (Rose 2007).

Assume that a disruptive event perturbs demand (perhaps directly, or perhaps as a forced demand reduction due to a supply shortage) in $m \leq n$ sectors. The worst-case demand perturbations in each of these m sectors is given by $c^\star_{l,\max}$, $l = \{1, \ldots, m\}$. The implementation of preparedness, or resilience-building, activities is concerned with reducing $c^\star_{l,\max}$ through efficient resource allocation. If r_l is a preparedness strategy adopted to reduce the initial sector l demand perturbation impact, the effectiveness of r_l is measured in terms of the new resulting demand perturbation in Eq. (3.6). All sector demand perturbations are governed by Eq. (3.7).

$$c^\star_l = f_l\left(c^\star_{l,max}, r_l\right) \tag{3.6}$$

$$c^\star_i = \begin{cases} c^\star_l & if\ i \in l \\ 0 & otherwise \end{cases} \tag{3.7}$$

Assuming a numerically higher value for r_l results in a more effective preparedness strategy, some candidate graphical relationships between $c_l^\star$ and r_l are conceptually depicted in Figure 3.2, with the upper bound being $c_{l,\max}^\star$.

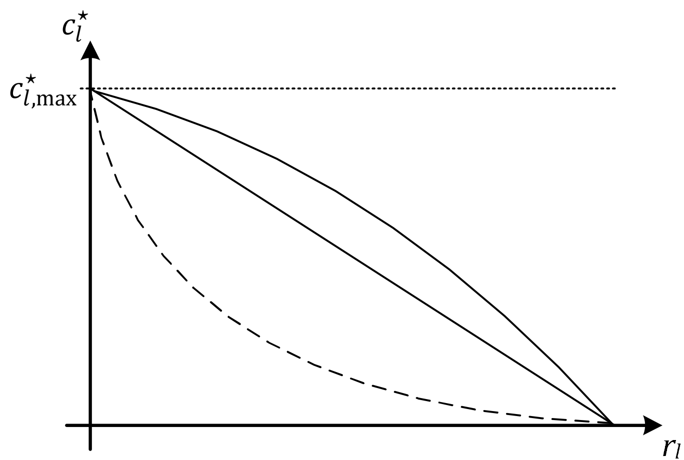


Figure 3.2. Candidate functional relationships between $c_l^\star$ and r_l.

Since implementing preparedness strategies comes at a cost, there is a finite budget that governs the maximum possible values taken by r_l. If $g_l(r_l)$ expresses the cost of implementing strategy r_l, then this budget as an upper bound. For the entire set of interdependent infrastructure and industry sectors, if at most budget b is available, then Eq. (3.8) is a constraint limits a fixed budget.

$$\sum_{l=1}^{m} g_l(r_l) \leq b \tag{3.8}$$

The collection of Eqs. (3.5), (3.6), and (3.8) results in the resource allocation optimization problem in Eq. (3.9).

$$\max_{c_l^\star, r_l} \frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^\star \left(c_{l,max}^\star - c_l^\star\right)}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^\star c_{l,max}^\star}$$

$$\begin{aligned} s.t.\quad & c_l^\star = f_l\left(c_{l,max}^\star, r_l\right), \forall l \in \{1,2,\dots,m\} \\ & \sum_{l=1}^{m} g_l(r_l) \le b \\ & r_l \ge 0, \forall l \in \{1,2,\dots,m\} \end{aligned} \tag{3.9}$$

Eq. (3.9) represents a generalized formulation of the resource allocation to maximize absorptive capacity. The functional forms of $f_l(\cdot)$ and $g_l(\cdot)$ govern the solution to the absorptive capacity planning problem. For macro-level planning, the r_l value might denote the amount of capital that can be invested in purchasing and substituting for the lost demand $c_l^\star$. If the exponentially decreasing functional form (the dotted line in Figure 3.2) is assumed, Eq. (3.10) would govern how planning for absorptive capacity can improve $c_l^\star$, where α_l is a measure of the effectiveness of investment r_l, which also shows the return for substituting for lost demand for sector *l*.

$$c_l^\star = c_{l,max}^\star e^{-\alpha_l r_l} \tag{3.11}$$

For this special case, the absorptive capacity planning optimization problem can be written as Eq. (3.12), given that Eq. (3.11) is a strict equality constraint. Note that r_l represents an investment made to improve absorptive capacity, therefore the sum of r_l must satisfy the budget constraint.

$$\max_{r_l} \frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^\star \left(c_{l,max}^\star - c_{l,max}^\star e^{-\alpha_l r_l}\right)}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^\star c_{l,max}^\star}$$

$$\begin{aligned} s.t.\quad & \sum_{l=1}^{m} r_l \le b \\ & r_l \ge 0, \forall l \in \{1,2,\dots,m\} \end{aligned} \tag{3.12}$$

3.3 Decision Making Under Uncertainty

Decision makers with interdependent economic impacts in mind, planning for absorptive capacity to harden industries facing human-made or natural disasters, must consider the uncertainty of the decision making environment (e.g., relationships among industries after a disruption). Uncertainty resulting from imperfect and/or unknown information can be characterized by: (i) inexactness, (ii) unreliability and (iii) ignorance. All of these could be caused by the lack of quality or appropriateness of data used as inputs to the model, an incomplete understanding of the modeled phenomena, and/or all omissions due to a lack of knowledge (Funtowicz and Ravetz 1990). Walker et al. (2003) provide a conceptual basis for a systematic treatment of uncertainty in model-based decision support activities such as policy analysis and risk assessment by defining three dimensions of uncertainty as the location of uncertainty ("where the uncertainty manifests itself within the model complex"), the level of uncertainty ("where the uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance"), and the nature of uncertainty ("whether the uncertainty is due to the imperfection of our knowledge or is due to the inherent variability of the phenomena being described"). The location of uncertainty refers to the logical structure of a generic system model within which various sources of uncertainty are classified as: (i) context in terms of identifying the boundaries of the system to be modeled, (ii) model uncertainty associated with both conceptual model and the analytical model, (iii) inputs to the model, (iv) parameters uncertainty, and (v) model outcome, as an accumulated uncertainty. The level of uncertainty, an expression of the scale of uncertainty, is defined as an entire spectrum of different levels of knowledge exists ranging from the complete understanding to total ambiguity categorized as: (i) determinism, (ii) statistical uncertainty, (iii) scenario uncertainty, (iv) recognized ignorance, and (v) total ignorance. And, nature of uncertainty could be either related to limited and inaccurate data, measurement errors, incomplete knowledge, limited understanding, imperfect models, subjective judgement, or ambiguities, classified as epistemic uncertainty, or inherent uncertainty or randomness induced by variation associated with external input data, input functions, parameters, and certain model structures, categorized as aleatory (variability) uncertainty.

In this work, data uncertainty in the integrated model in Eq. (3.12), consisting of data used to parameterize the IIM and resource allocation, is considered. As the coefficients of the $\mathbf{A}^{\star}$ matrix derived from the technical coefficient matrix $\mathbf{A}$, they are subject to uncertainties arising from the inter-industry data collection efforts by the BEA. The BEA collects annual input-output records for a group of 15 aggregated industries and more detailed records for 65 industries every five years. As the $\mathbf{x}$ vector is derived from the same BEA data, it is prone to the same uncertainties as $\mathbf{A}^{\star}$. Hence the economic input-output model, and subsequently the IIM, is prone to uncertainties arising from parameterizing interdependency coefficients matrix $\mathbf{A}$ (and $\mathbf{A}^{\star}$)and $\mathbf{x}$ vector of total output, due to statistical errors in compiling massive data bases and the variant nature of these parameters over time (Bullard and Sebald 1977, West 1986). Barker (2008) and Barker and Haimes (2009) addressed uncertainty in the interdependency matrix $\mathbf{A}^{\star}$ particularly in the IIM. The inexactness in quantifying the effectiveness of investments within the resource allocation model should also be recognized (MacKenzie and Zobel 2016). Hence, the optimization model formulated in Eq. (3.12) contains epistemic data uncertainty in estimation of (i) the $\mathbf{A}^{\star}$ matrix and magnitude of $\mathbf{x}$ vector and (ii) α_l as the measure of the effectiveness of investment r_l in industry l.

Bullard and Sebald (1977) studied inherent uncertainties in the coefficients of $\mathbf{A}$, $\mathbf{x}$, and $[\mathbf{I}-\mathbf{A}]^{-1}$ as bounded within a small interval of the published values. Similarly, our approach is to consider small random noises to model data point uncertainties in $\mathbf{x}$ and $\mathbf{D}^{\star}=[\mathbf{I}-\mathbf{A}^{\star}]^{-1}$, whose elements are $d_{ij}^{\star}$. Furthermore, to model uncertainty in defining α_l, the investment effectiveness for industry l, we propose probabilistic treatment considering the optimistic, pessimistic, and most likely estimates of α_l.

We propose a robust formulation of the optimization problem of Eq. (3.12). This robust formulation is shown in Eq. (3.13) , where *D*, *X*, and Ψ are uncertainty sets that contain all possible realizations of respective matrices and vectors. It is assumed that the sets *D* and *X* contain bounded random variations (e.g., ±5%) of the values of $\mathbf{D}^{\star}$ and $\mathbf{x}$, respectively. A triangular distribution represents the set ψ.

$$\begin{aligned} max \quad & f \\ s.t. \quad & \left[\frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}\left(c_{l,max}^{\star}-c_{l,max}^{\star}e^{-\alpha_l r_l}\right)}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}c_{l,max}^{\star}}\right] \geq f \\ & \sum_{l=1}^{m} r_l \leq b \\ & r_l \geq 0, \forall l \in \{1,\ldots,m\} \\ & D^{*} \in D, x \in X, \alpha \in \Psi \end{aligned} \tag{3.13}$$

The non-linearity and stochasticity of the proposed model makes it difficult to solve analytically. As such, rather than guaranteeing a certain level of absorbability, being extremely conservative in Eq. (3.13), we want to make sure that the proposed model suggests a resource allocation set such that guarantees an absorbability that holds with probability $(1-\varepsilon)$ for small $\varepsilon>0$. The term ε is referred to as value-at-risk in portfolio optimization and has been widely used in "soft" robust optimization (Shapiro et al. 2009, Ben-Tal et al. 2009, Rockafellar and Uryasev 2000). The final formulation, presented in Eq. (3.14), is tractable using different simulation-based optimization solvers.

$$
\begin{aligned}
max \quad & f \\
s.t. \quad & Pr\left(\left[\frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}\left(c_{l,max}^{\star} - c_{l,max}^{\star} e^{-\alpha_l r_l}\right)}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star} c_{l,max}^{\star}}\right] \geq f\right) \geq 1 - \epsilon \\
& \sum_{l=1}^{m} r_l \leq b \\
& r_l \geq 0, \forall l \in \{1, \dots, m\} \\
& D^{*} \in D, x \in X, \alpha \in \Psi
\end{aligned}
\tag{3.14}
$$

3.4 Illustrative Example: Inland Waterway Port Infrastructure Disruption

The proposed planning model for absorptive capacity is applied to a case study of the Port of Catoosa in Tulsa, Oklahoma. The Port of Catoosa is connected to the U.S. inland waterway network through the McClellan-Kerr Arkansas River Navigation System, a part of the Mississippi River Navigation System. There are approximately 70 companies using the port and an annual freight volume of 2.2 million tons is sent and received through the port (US Army Corps of Engineers 2010, Commodity Flow Survey 2010, Tulsa Port of Catoosa 2010). As defined by the North American Industry Classification System (NAICS), 62 industries operate in Oklahoma, therefore the $\mathbf{A}^{\star}$ matrix regionalized for Oklahoma is 62×62. This case study will focus on the six industries that are the port's largest exporters (listed in Table 3.1) in terms of commodity flows due to high trade figures reported by Bureau of Transportation Statistics (2010). In this study, the enhancement of the absorptive capacities of these six industries is analyzed.

Table 3.1. Six primary industries using the Port of Catoosa, along with their NAICS codes.

Industry name	NAICS code
Food, beverage, and tobacco products	311
Petroleum and coal products	324
Chemical products	325
Nonmetallic mineral products	327
Machinery	333
Miscellaneous manufacturing	339

The exports through the Port of Catoosa contribute to the external demand of the industries in Oklahoma. As such, in case of a disaster at the port resulting in the loss of exports, there is a demand perturbation in the industries that use the port. Due to the interdependence among industries, the cascading of the demand perturbations causes losses to all the other state industries. Assuming that, in the case of a disruptive event, the only losses in the state economy are due to the loss of exports through the port, we can obtain estimates of the maximum demand perturbations, $c^{\star}_{l,\max}$, for the six primary industries using the port. These are found for each industry as the ratio of that industry's mean estimate of exports to its total economic output, all provided in Table 3.2. It is further assumed that industries not using the port have zero demand perturbations, though could suffer from interdependent inoperability.

Table 3.2. Maximum demand perturbation for the major industries using the Port of Catoosa in 2007 (output and exports given in million USD).

Industry name	Exports	Output	$c^{\star}_{l,\max}$
Food, beverage, and tobacco products	140.0	5578.5	0.0251
Petroleum and coal products	57.0	12644.0	0.0045
Chemical products	89.0	1327.3	0.0671
Nonmetallic mineral products	3.0	2026.2	0.0015
Machinery	108.0	7174.4	0.0151
Miscellaneous manufacturing	6.0	746.6	0.0080

A policy maker caring about the economy of the state of Oklahoma may seek a best way to allocate a limited budget to individual industries in order to let them invest in planning for absorptive capacity to avoid the maximum demand perturbation during the port closure. Depending on the industry faced with the disruptive event, this resource could describe: (i) maintaining additional inventory to maintain productivity, and (ii) setting short-term coordination contracts with distributors to be ready for alternative transportation modes other than the port.

The model assumes that allocating resources reduces the impact exponentially. As more resources are allocated to an industry, the impacts on an industry decline at a constantly decreasing rate, and investing an additional dollar to reduce risk returns less benefit than investing the first dollar. For each directly impacted industry, the exponential function, shown in Eq. (12) requires estimating an investment effectiveness parameter, α_l. This parameter can be assessed if r_l, the amount of resources needed to reduce the direct impacts on industry l by a fraction $c_l^\star/c_{l,\max}^\star$, is known or can be estimated, since $\alpha_l = -\frac{\log(c_l^\star/c_{l,\max}^\star)}{r_l}$. While the value of α_l is always non-zero and positive with no upper bound, it is expected that α_l would be small for large-scale disruptions where millions of dollars are necessary to reduce the impact.

Table 3.3 lists parameter estimates for the effectiveness of investments, α_l, in planning for absorptive capacity in different industries considering the consequences on reducing the maximum demand perturbation by 50%, i.e., setting $\frac{c_l^\star}{c_{l,\max}^\star} = 0.5$. *Food and beverage products* would be affected dramatically by the closure of the Port of Catoosa considering estimates for the cost per ton-mile for a barge at \$0.97, compared to \$2.53 for rail, and \$5.35 for trucking (Arkansas Waterway Commissions 2014), together with the distances to the general customers for the products of this industry, it is assumed that on average \$7 million USD should be invested to avoid the maximum demand perturbation in this industry by 50%. Direct impacts for *Petroleum and coal products* is much less than *Food and beverage products*, but the nature of this industry's products makes it difficult to look for alternative transport modes. And long-term investments in increasing domestic demand by developing refining facilities, pipelines, and alternate transportation infrastructures could be effective and result in a higher absorptive capacity. As such, α_2 is calculated assuming that an almost \$5 million USD investment is needed to decrease the maximum demand perturbation in petroleum industries by half. The investment effectiveness for the other four industries are estimated considering the maximum loss in each industry and the options to increase the absorptive capacity with potential contracts for alternative transportation modes.

Table 3.3. Estimates for the cost-effective parameter α_l (given as per million USD).

l	Industry name	α_l
1	Food, beverage, and tobacco products	0.0460
2	Petroleum and coal products	0.0631
3	Chemical products	0.3419
4	Nonmetallic mineral products	0.2014
5	Machinery	0.0836
6	Miscellaneous manufacturing	0.4257

3.4.1 Planning for Absorptive Capacity

The proposed model in Eq. (3.12) is implemented to optimize the budget allocation among the six important industries that trade through the Port of Catoosa. Four different total budget amounts are considered for allocations across the six industries: \$10 million, \$20 million, \$30 million, and \$40 million, all in USD.

Table 4 shows the results from solving Eq. (3.12), in terms of the budgets r_l allocated to individual sectors. We see that to maximize the absorptive capacity of the whole interdependent economy: (i) at the smallest budget allocation of \$10 million most of the resources are distributed to Miscellaneous manufacturing (339) and Chemical products (325); (ii) as the budget allocation is increased towards \$40 million the resources get distributed towards Food and beverage and tobacco products (311) and Machinery (333); and (iii) Petroleum and coal products (324) comparatively require some resource allocations when budgets are increased to \$30 million and beyond; (iv) Nonmetallic mineral products (327) comparatively require very little resource allocations. These results make sense as, based on Table 2 data, Food and beverage and tobacco products (311) and Machinery (333) are the two highest exporters through the port, so to progressively maximize the absorptive capacity of the economy most of the budget allocations will be distributed towards restoring economic flows in these sectors. Miscellaneous manufacturing (339) and Chemical products (325) have high initial resource allocation values because their cost effectiveness parameters α_l from Table 3 are high. But this means these is a fast stabilization of absorptive capacities in these sectors at the initial investment of \$10 million, and subsequently these sectors requires smaller increments of the resource allocations to further maximize the absorptive capacity of the economic system. Table 3.5 confirms the above, as indicated by the values of the absorptive capacities of individual sectors as budget allocations are increased.

Also shown in Table 3.5 are the values of the total economic losses avoided and the level of absorptive capacity achieved (value of the objective function of Eq. (3.12)) corresponding to each level of budget allocation. First we see that if no budget allocations were made then there is an economic loss of \$69.3 million USD to the six industries, which is estimated from Table 5 by summing the economic loss values for these sectors.

Overall the whole economy has a loss of $146.6 million. These results show the interdependent effects of the IIM. A budget allocation of $10 million results in decreasing economic losses by $37.9, which is a 25.8% restoration of absorptive capacity. Similarly a budget allocation of $40 million decreases the economic losses by $84.8, thereby restoring absorptive capacity by 57.8%.

We note from the Table 3.5 results that for every subsequent $10 million increment of budget allocation results in diminishing returns in terms of the value of economic loss avoided or absorptive capacity restored. For example, from Table 5 as budget allocation is increased from $10 million to $20 million the changes in total loss avoided is $19.8 million, whereas an increment of budget allocation from $30 million to $40 million results in changing the amount of losses avoided by $12.2 million. Hence the decision maker has to make a tradeoff between increasing budget allocations and the amount of changing in losses avoided. A point to stop would be when the increment in budget allocation is more than the value by which the loss is reduced.

As shown in Table 3.4, allocating absorptive capacity to Nonmetallic mineral products (327) is not as beneficial as investing money in the five other industry, and if the total budget is $20 million dollars or less, the policy maker should not devote any resources to Petroleum and coal products (324). Also, by increasing the total budget limit, a smooth increase in the amount of resources should be invested in Miscellaneous manufacturing (339) and Chemical products (325). On the other hand, there are varied ascending/descending trends in the percentage of incremental investment devoted to Food and beverage and tobacco products (311) and Machinery (333).

Table 3.4. Resource allocation for absorptive capacity in different industries (in million USD).

	Resources allocated to each industry for each total budget			
Industry name	10	20	30	40
Food, beverage and tobacco products	0.307	5.885	10.952	14.917
Petroleum and coal products	0.000	0.000	0.917	3.807
Chemical products	3.879	4.630	5.311	5.845
Nonmetallic mineral products	0.000	0.000	0.000	0.000
Machinery	2.784	5.853	8.640	10.822
Miscellaneous manufacturing	3.029	3.632	4.179	4.608

As shown in Figure 3.3 and the complementary Table 3.4, investment of $30 million to harden the five industry sectors among the six most important to the port can avoid the maximum economic loss in Oklahoma by up to 50%, and it indirectly protects *Nonmetallic mineral products* (327) though the policy maker does not devote resources directly to this industry. Further, for example, nearly $40 million in economic losses across the Oklahoma economy can be avoided with a $10 million investment in absorptive capacity in the six key industries, according to the model.

Table 3.5. Economic loss under different total budget plans (budgets, and losses in million USD).

Industry name	Economic loss (no investment)	Proportion of economic loss avoided for each total budget 10	20	30	40
Food, beverage, and tobacco products	25.897	0.019	0.240	0.398	0.499
Petroleum and coal products	12.589	0.070	0.090	0.151	0.292
Chemical products	16.464	0.718	0.780	0.825	0.854
Nonmetallic mineral products	1.045	0.090	0.164	0.219	0.259
Machinery	20.317	0.209	0.387	0.514	0.595
Miscellaneous manufacturing	18.878	0.588	0.675	0.738	0.781
Total economic loss	146.6268	108.738	88.8825	73.984	61.7947
Total economic loss avoided	-	37.9	57.7	72.6	84.8
Total absorptive capacity	-	0.258	0.394	0.495	0.578

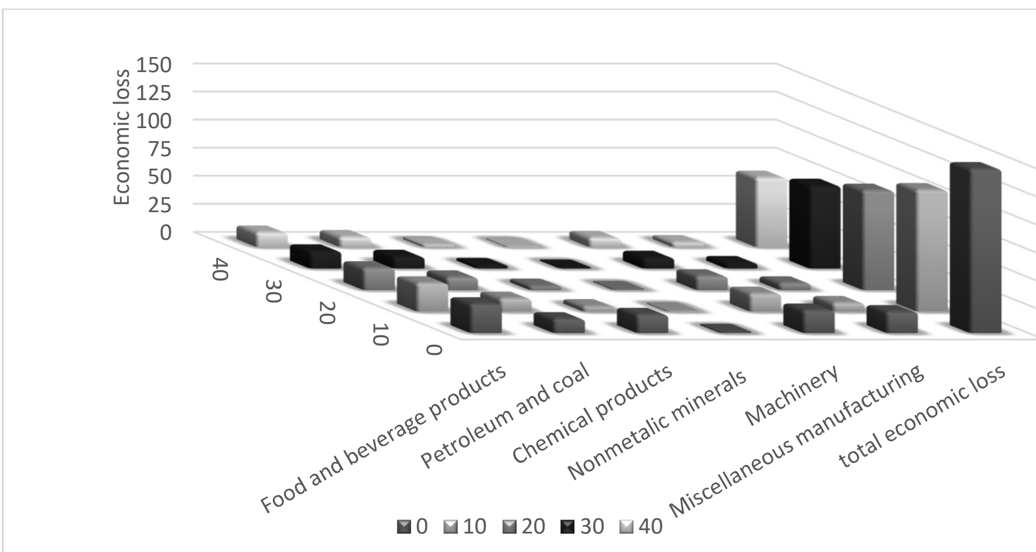


Figure 3.3. Economic loss for each of the six industries and Oklahoma for each total budget.

Figure 3.4 shows the extent to which each industry sector and the Oklahoma economy are able to absorb shocks from a port disruption by allocating a defined amount of budget to harden the most important industry sectors in the area.

3.4.2 Planning for Absorptive Capacity

Discussed in Section 3.3, epistemic uncertainty in estimating (i) the $\mathbf{A}^{\star}$ matrix and magnitude of $\mathbf{x}$ vector, and (ii) α_l as the measure of the effectiveness of investment r_l in industry l, should be accounted for in this study. In this case study, small amounts of perturbations are considered to model data uncertainties in $\mathbf{x}$ and $\mathbf{D}^{\star} = [\mathbf{I} - \mathbf{A}^{\star}]^{-1}$, whose elements are $d_{ij}^{\star}$. It is assumed that the elements insets X and D related to the six industry sectors contain bounded random variations to the amount of ±5% of the (deterministic) values of $\mathbf{x}$ and $\mathbf{D}^{\star}$, respectively. Furthermore, a probabilistic treatment considering the optimistic, pessimistic, and most likely estimates of α_l with a triangular distribution is assumed to model uncertainty in the investment effectiveness for industry l. The parameters of these triangular distributions are shown in Table 3.6. We model the uncertainty in this problem using Frontline Solvers, an optimization and simulation application for Microsoft Excel.

Table 3.6. Probabilistic treatment estimating the cost-effective parameter α_l.

		α_l		
l	Industry name	Min	Mode	Max
1	Food, beverage, and tobacco products	0.0240	0.0460	0.0570
2	Petroleum and coal products	0.0400	0.0631	0.0700
3	Chemical products	0.1000	0.3419	0.4000
4	Nonmetallic mineral products	0.0900	0.2014	0.3000
5	Machinery	0.0600	0.0836	0.0900
6	Miscellaneous manufacturing	0.2000	0.4257	0.5000

Table 3.7, which summarizes the solutions of Eq. (3.13), shows how epistemic data uncertainty, simulated with 1000 replications, affects the total economic losses resulting from each total budget. The differences between 5^{th} and 95^{th} percentiles of simulated results is 9 to 12 U.S. million dollars, in the cases of the four different budget limits. Hence, it is desired to consider the data uncertainty in decision making for allocating the limited budget to harden the six industry sectors within the state of Oklahoma. As the standard deviation shows, in the four simulated cases in Table 3.7, the amount of variation or data dispersion due to the uncertainty is at least \$3 million, highlighting the importance of accounting for uncertainty in decision making.

Implementing the proposed soft-robust optimization model in Eq. (3.14), $\varepsilon = 0.05$ is considered to guarantee an absorbability that holds with probability of $(1 - \varepsilon = 95\%)$. Comparing (i) the resource allocation resulting from the data uncertainty shown in Table 3.8, with (ii) the results from the deterministic model shown in Table 3.4, the allocation differences are generally less than 10%. Some exceptions include *Food and beverage and tobacco products* (311), which experiences a 100% decrease when the total budget is 10 million and subsequently has lesser budget allocations compared to the Table 3.4 values. Similarly *Petroleum and coal products* (324), encounters decreases in allocated resources and that varies for different total budget amounts. Comparatively *Chemical products* (325), *Miscellaneous manufacturing* (339), and *Machinery* (333) see increases in budget allocations in that order. These changes, though small, show how uncertainty can alter the resource allocations. Figure 3.4 shows the 95% confidence interval estimates for total losses in the Oklahoma economy expected when the each total budget is allocated across the six industries.

Table 3.7. Probabilistic treatment estimating the cost-effective parameter α_l.

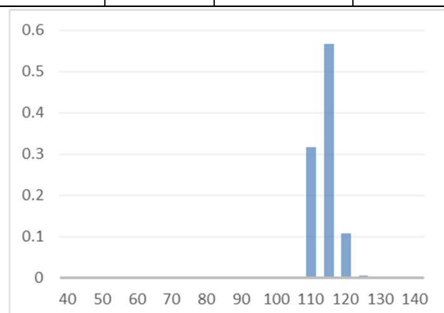
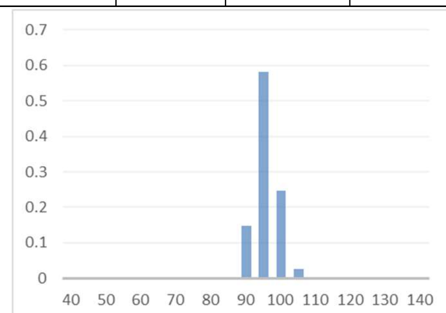
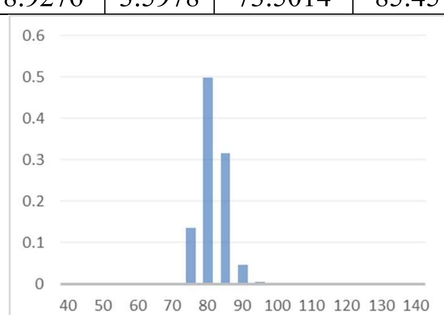
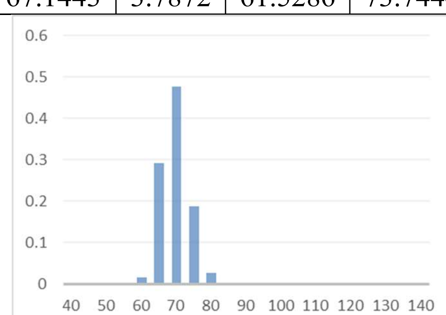
		Budget limit (U.S. million dollars)							
		10				20			
Total economic loss (U.S. million dollars)	Epistemic data uncertainty	Mean	Std. Deviation	5th Percentile	95th Percentile	Mean	Std. Deviation	5th Percentile	95th Percentile
		111.4919	2.9967	107.2106	116.9517	93.2697	3.2179	88.5499	99.0821
									
	Deterministic			108.738		Deterministic			88.8825
		Budget limit (U.S. million dollars)							
		30				40			
Total economic loss (U.S. million dollars)	Epistemic data uncertainty	Mean	Std. Deviation	5th Percentile	95th Percentile	Mean	Std. Deviation	5th Percentile	95th Percentile
		78.9276	3.5978	73.5014	85.4518	67.1443	3.7872	61.5286	73.7444
									
	Deterministic			73.984		Deterministic			61.7947

Table 3.8. Resource allocation for absorptive capacity in different industries considering uncertainty (in million USD).

	Resources allocated to each industry for each total budget			
Industry name	10	20	30	40
Food, beverage, and tobacco products	0	5.344	10.712	14.562
Petroleum and coal products	0	0	0.231	3.071
Chemical products	4.102	4.964	5.830	6.433
Nonmetallic mineral products	0	0	0	0
Machinery	2.708	5.844	8.730	10.983
Miscellaneous manufacturing	3.191	3.848	4.498	4.952
Total budget	10	20	30	40

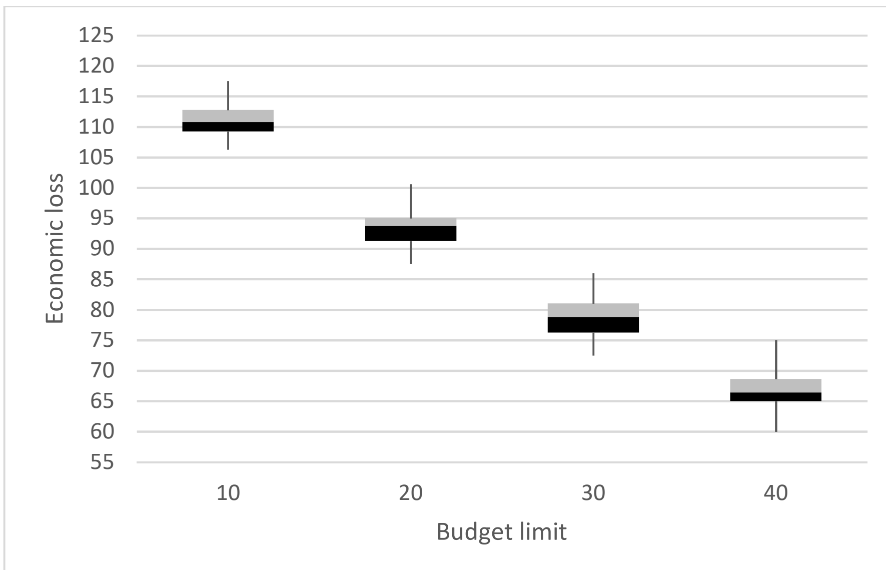
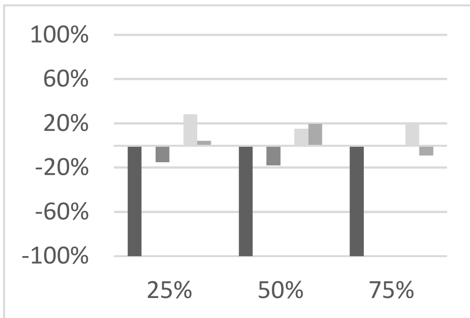
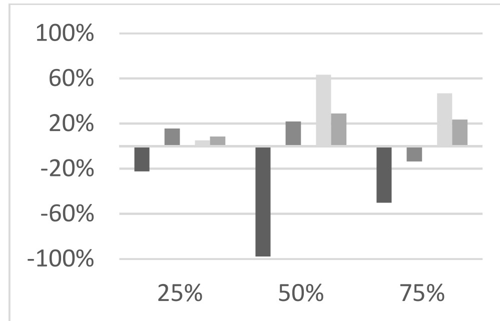


Figure 3.4. 95% confidence interval estimates of total economic loss under different budget limits, million USD.

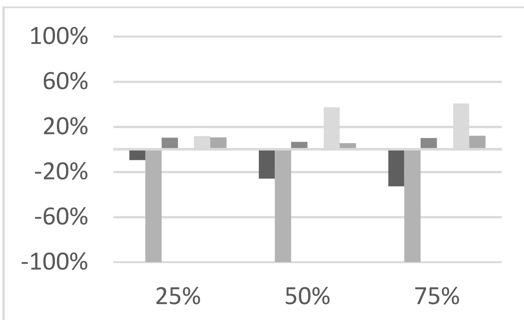
Measure of the effectiveness of investment α_l is considered to monitor the effects of changes in the data uncertainty on budget allocation. Figure 3.6 illustrates the changes in the resulting allocated budget to each industry when the interval in probabilistic treatment of α_l is increased by 25%, 50%, and 75%. These three incremental levels of uncertainty are deployed by changing the upper and lower limits shown in Table 3.6 while the mode values are kept constant. The percentage of changes in budget allocation comparing with the results of the deterministic model, for different budget limits, are plotted.



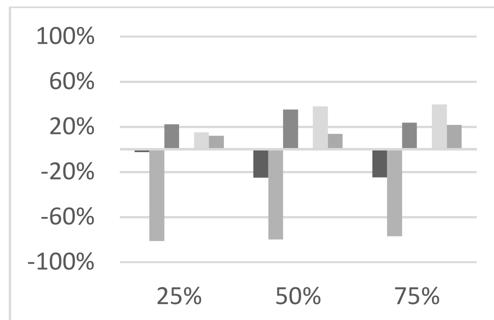
(a) total budget of $10 million



(b) total budget of $20 million



(c) total budget of $30 million



(d) total budget of $40 million

Figure 3.5. Percentage of changes in budget allocation with increasing interval width (25%, 50%, 75%) for the probabilistic treatment of the investment effectiveness parameter α_l.

As shown in Figure 3.5 different behavior in percentage of the changes in allocating budget to the six industries are monitored based on the total budget limits and the magnitude of the change in the uncertainty interval. For example, significant decreases are seen in the budget that should be allocated to *Food and beverage and tobacco products* (311) when the total budget is less than $20 million, which is comparable to the results from the deterministic model. Smooth changes are seen for the allocated budget to *Chemical products* (325). Also, a recognizable change exists in

Petroleum and coal products (324) when the total budget limit is more than $20 million, where an increase in the uncertainty interval decreases the budget that should be allocated. In general, it can be seen that the larger uncertainty interval for investment effectiveness caused more changes in budget allocation for higher budget limits.

3.5 Concluding Remarks

Freight transportation infrastructure plays an important role as a facilitator of economic productivity by connecting industries from multiple regions. Large-scale disruptive events can cause failures within the system that propagate through the multiple interconnected industries. Investing in hardening both the infrastructure (e.g., backup equipment) and industries themselves (e.g., on-hand inventory) can lessen the effects of disruptions. The interdependent nature of industries must be considered when considering such resource allocation. This work discusses a modeling and analysis framework to allocate limited resources to harden industry sectors to enhance the absorptive capacity of the total economy.

The interdependent adverse effects of a disruption are measured using a risk-based interdependency model and an exponential resource allocation model is introduced to formulate the risk reduction. Considering the three components of resilience capacity identified by Vugrin and Camphouse (2011) and the notion of static resilience proposed by Rose (2009), a measure of absorptive capacity as the ability of the system to absorb the effects of a disruption is proposed. Finally, in an integrated optimization model, it is sought to maximize the whole system absorbability by allocating a limited budget to harden different industries. Further, sources of epistemic data uncertainty in the interdependency model has been considered and a soft-robust optimization model is developed to help policy makers to allocate resources under uncertainty.

The proposed modeling and analysis framework is implemented in case study developed based on the six important industries at the Port of Catoosa that use the inland waterway to send out commodities to their consumers out of the state of Oklahoma. Results show how increasing the budget limit affects allocated budget to each industry. Though Miscellaneous manufacturing (339) and Chemical products (325) receive the largest share with the $10 million budget, Food and beverage and tobacco products (311) and Machinery (333) receive the largest share as the budget allocation is increased to $40 million. It has been seen that considering bounded random variations to the amount of ±5% of the (deterministic) values of $\mathbf{x}$ and $\mathbf{D}^{\star}$ together with a probabilistic treatment considering the optimistic, pessimistic, and most likely estimates of α_l causes dramatic variation in the economic loss considering the allocated budget. Also, analysis on the measure of effectiveness showed that when the interval in the probabilistic treatment of α_l is increased by 25%, 50%, and 75%, the changes in the allocated budget varies in different budget limits. For example, While Food and beverage and tobacco products (311) experienced a significant decrease in the allocated budget when the total budget is less than $20 million, it faces at most a 30% decrease when the total budget is $40 million.

The proposed model can be implemented in a network of freight infrastructure and the multi-regional impacts of the disruption can be considered in both modeling the failure propagation and investing for absorptive capacity.

CHAPTER 4

PLANNING FOR ADAPTIVE CAPACITY

4.1 Introduction

The use of the term "resilience" has increased substantially in the literature in recent years (Mattson and Jenelius 2015, Hosseini et al. 2016, Kamalahmadi and Parast 2016), recognizing a shift in planning from prevention and protection to preparing for the inevitability of disruption. Several qualitative and quantitative frameworks being proposed to describe the resilience of a system (e.g., Patterson et al. (2006), Zobel (2011), Sarre et al. (2014)). While most definitions of resilience recognize the time-dependent nature of withstanding and recovering from a disruption, Rose (2004) defined *static resilience* as "the ability of an entity or system to maintain function when shocked." This is depicted in Figure 4.1, where $\%\Delta DY^{max}$ represents the maximum percentage change given the worst-case level of performance following a disruptive event, and $\%\Delta DY$ represents the actual percentage change in the performance of the system (assuming the implementation of a mitigation strategy) (Rose 2009). The original application of static resilience, as well as several subsequent studies (e.g., Rose (2007, 2009), Rose and Wei (2013), Hallegatte (2014), Pant et al. (2014), Baghersad and Zobel (2015)), deal with economic disruption. Mathematically, static resilience is measured in terms of the maximum potential drop in system performance and the estimated performance drop, as shown in Eq. (4.1). This quantitative approach is used in this study to define a performance measure for post-disaster rerouting, though we prefer the term adaptive capacity rather than static resilience.

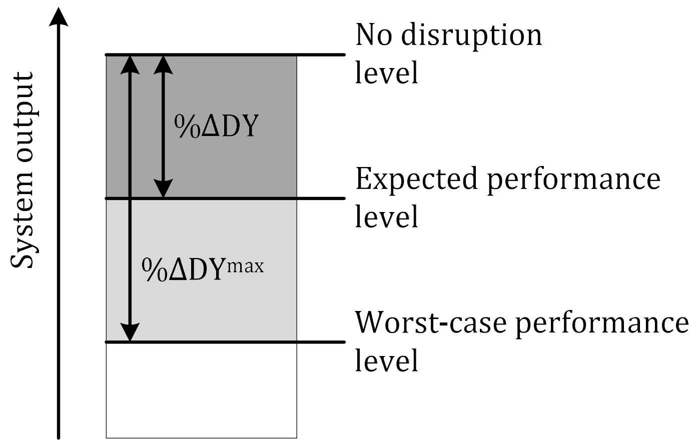


Figure 4.1. The performance components of static resilience (Rose 2009, Pant et al. 2014b).

$$static\ resilience = \frac{\%\Delta DY^{max} - \%\Delta DY}{\%\Delta DY^{max}} \tag{4.1}$$

Faturechi and Miller-Hooks (2015) thoroughly review the literature on transportation system performance considering disruptions to physical infrastructure. Defining a four-phase disaster life cycle as (i) mitigation, (ii) preparedness, (iii) response, and (iv) recovery, they suggest that most work focuses on assessing the transportation system's ability to deal with disruption consequences, with less work assessing strategies to manage the system after the disruption. Further, the literature that seeks rerouting strategies to mitigate the effects of disruption by maintaining freight flow through a residual network is sparse (Khaled et al. 2015, Gedik et al. 2014). And, to the author's knowledge, the approach proposed here to reroute flow and plan for adaptive capacity by considering the contribution of transportation network components to multi-industry impacts is non-existent in the literature. To address this gap in the literature, we propose an integrated optimization formulation to reroute commodities through the residual network to decrease the effect on local industries requiring those commodities for production. To do so, we combine a multi-commodity network flow formulation of a multi-modal transportation network with a risk-based multi-industry impact model in an integrated formulation.

4.2 Methodological Background

A disruption within a freight transportation network affects its vital role in transporting raw materials among manufacturers and final products between manufacturers and consumers. Such a disruption in the flow of commodities leads to economic losses across multiple industries. To devise an adaptive capacity strategy (i.e., post-disruption rerouting) to lessen total economic losses following a disruption, we propose an optimization framework that integrates (i) a multi-commodity network flow model of freight movement, (ii) a risk-based interdependency model of multi-industry impacts, and (iii) an objective function that addresses adaptive capacity with a measure of static economic resilience (Rose 2009, 2013, Pant et al. 2014b). The proposed optimization model is developed following a three-step approach, illustrated in Figure 4.2.

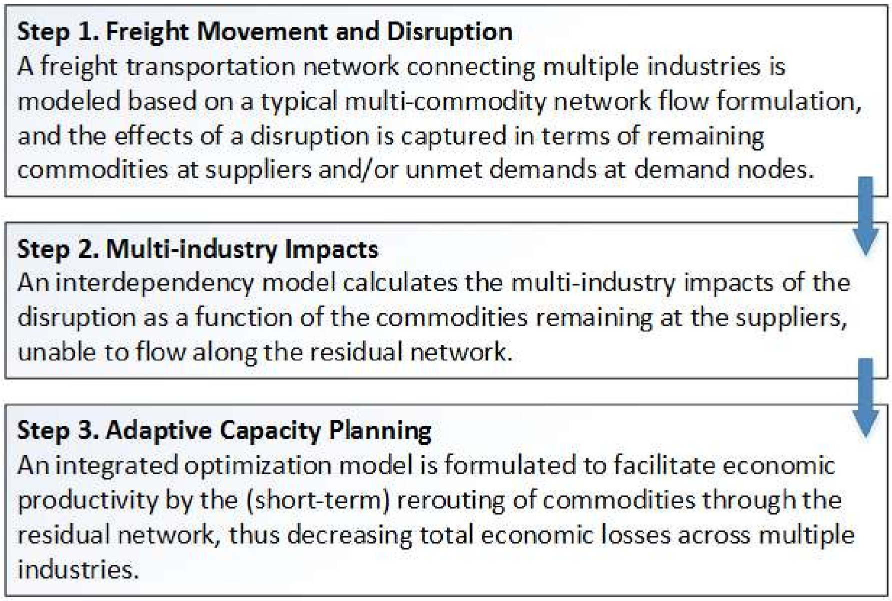


Figure 4.2. Three-step approach to planning for adaptive capacity with multi-industry impacts.

4.2.1 Freight Movement and Disruption

From a tactical point of view, integrating (i) industries and (ii) their supply capabilities or demand requirements together with (iii) the structure of the transportation network, can result in a minimum cost MCNF model that can route commodities from suppliers to demand nodes via f_{ij}^{k}, collectively representing the flow of commodities on the links of a baseline (undisrupted) network. Natural hazards, human-made events, or common failures could threaten the functionality of the network components and consequently interrupt commodity flows. The consequences of a hazards, attacks, or failures are simulated as disruptions in the flow of valuable goods or services through the network caused by disabling network components. The functionality of the network is analyzed to determine how vulnerable it is to interdiction, and which nodes or links, if lost, result in the most damage to network performance. Interdiction analyses encompass a wide range of possible disruptions that may vary with respect to spatial scales, correlation of disruptive events, sequence of failures, and event duration.

In the case of any disruption modeled as the removal of a network component or a set of components (or a drop in functionality of the network modeled as reduction of link capacities, u'_{ij}), the consequences are sought by deducting the commodity flows on the affected links from the baseline flow. Let $G' = (N', L')$ represent the network after disruption with updated sets of links, L' and nodes, N'. The sets N'_{-}, N'_{+}, N'_{0} denote the post disruption sets of nodes associated with home of consumers, home of suppliers, and transshipment nodes, respectively. The quantity of commodity k at node i that is either undelivered and remaining with the suppliers, or unsatisfied demand of consumers, is reflected in the slack variable S_i^k. This slack variable will be used subsequently to drive the calculation of inoperability among multiple industries. It is assumed that each type of commodity represents the output of a lone industry, and interdependent inoperability propagated through a set of industries caused by unsatisfactory demands/supplies will be modeled in the next section.

4.2.2 Multi-industry Impact

In this work, we use an extension of the input-output economic model, for which Wassily Leontief (1966) won a Nobel Prize, to capture the multi-industry impacts of unmet demands at demand nodes and remaining commodities at supply nodes as the result of a disruption to components of the transportation network. In addition to industry inoperability, a traditional economic loss metric can be calculated by multiplying each industry's production level, x_k, in dollars, by its inoperability level: for industry k, $Q_k = x_k q_k$. Such a measure can also be expressed for the collection of K industries, $Q = \mathbf{x}^T \mathbf{q}$.

As such, decisions to plan for adaptive capacity can be made with respect to economic impact across multiple industries.

4.2.3 Planning for Adaptive Capacity

Adaptive capacity is considered to be the extent to which a freight transportation network is capable of facilitating economic productivity by the (short-term) rerouting of commodities through the residual network to reduce remaining commodities at suppliers and unsatisfied demand at consumers. Inoperability in industry k is calculated with Eq. (2.2), and economic losses for industry k can be found by multiplying the proportional inoperability by expected production level in monetary units, $Q_k = x_k q_k$. Economic losses for the entire set of industries is calculated with $Q = \mathbf{x}^T\mathbf{q}$. As such, inoperability or economic impact at the industry level, or total economic impact at the across all industries, can be used to valuate strategies for strengthening adaptive capacity. Proposed in Eqs. (4.2) and (4.3) are two such metrics motivated by Eq. (4.1).

When planning emphasis is placed on a particular industry (i.e., rerouting freight in the transportation network to reduce the impact to industry k), Eq. (2.2) is proposed to valuate a strategy to strengthen adaptive capacity. Term $Я_e^k$ is a proportional measure involving (i) the economic loss, Q_e^k, experienced by a particular industry k following disruptive event e when no adaptive capacity planning is taken and (ii) the economic loss, Q_R^k, in industry k when a strategy is taken to avoid the maximum economic loss in that particular industry.

$$Я_e^k = \frac{Q_e^k - Q_R^k}{Q_e^k} \tag{4.2}$$

For a perspective that spans all industries, Eq. (2.3) provides a similar proportional metric, where Q_e is the multi-industry economic loss caused by disruption e in the baseline case, and Q_R is the multi-industry loss when a rerouting strategy is taken to avoid the maximum economic loss.

$$Я_e^R = \frac{Q_e - Q_R}{Q_e} \tag{4.3}$$

Assuming a multi-industry perspective and considering a hypothetical decision maker interested in limiting economic losses across multiple industries, Eq. (4.3) serves as the objective function in the following optimization framework that integrates the multi-commodity network flow model from Section 4.2.1 and the Inoperability Input-Output Model from Section 4.2.2 Following a particular disruption e that affects a particular set of transportation links, the proposed model in Eqs. (4.4)-(4.12) seeks to optimally reroute the flow of commodities through the residual network such that a measure of static economic resilience is minimized. Here, it is assumed that the result of the model provides decision makers with a rerouting strategy across different modes. The period of disruption is assumed to be sufficiently long enough to employ intermodal container scheduling models (e.g., Lee and Kim (2010), Wang and Yun (2013)) to devise operational-level plans based on the resulted contingent rerouting strategy in the simplified static supply-demand network. Notation employed in the problem formulation is summarized as follows, noting that network variables (e.g., the sets of links and nodes) with a prime as superscript are related to the network after disruption, referred to as the residual network.

Parameters

L'	set of links	N'	set of nodes
N'_k	set of nodes related to industry *k*	u'_{ij}	capacity of link (i, j) after disruption
N'_0	set of transshipment nodes	q_k	inoperability of industry *k*
N'_-	set of nodes that are home to consumers	N'^{α}_-	set of nodes that are home to consumers in the region of interest α
N'_+	set of nodes that are home to suppliers	N'^{α}_+	set of nodes that are home to suppliers in the region of interest α
γ_i	intermediate variable to keep the slack at node *i* positive	b'^k_i	mass-balance variable representing demand/supply/transshipment at node *i* after disruption
μ_k	binary coefficient with value 0 when no unsatisfied demands at demand nodes and 1 when at least one demand node with unsatisfied needs	S^k_i	slack variable that captures undelivered commodity *k* remaining with the supplier node *i* or unsatisfied demand at demand node *i*
$a^{\star}_{rk}$	elements of the normalized interdependency matrix $\mathbf{A}^{\star}$	$c^{\star}_k$	final consumption perturbation for industry *k*
x_k	production level of industry *k* in monetary value		

Decision variable

f'^k_{ij}	integer variable represents the flow of commodity k across link (i, j) in the network after disruption

Based on this notation, planning for adaptive capacity by rerouting the flow of commodities through the residual network is formulated as follows.

$$\max \ Я_e^R \tag{4.4}$$

s.t.

$$\sum_{k=1}^{K} f_{ij}^{\prime k} \leq u_{ij}^{\prime} \ \forall \, (i,j) \in L' \tag{4.5}$$

$$\sum_{(i,j)\in L'} f_{ij}^{\prime k} - \sum_{(j,i)\in L'} f_{ji}^{\prime k} + \gamma_i S_i^k = b_i^{\prime k} \quad k = 1,\ldots,K \tag{4.6}$$

$$\gamma_i = \begin{cases} -1 & \text{for } i \in N_-' \\ +1 & \text{for } i \in N_+' \\ 0 & \text{for } i \in N_0' \end{cases} \tag{4.7}$$

$$c_k^\star = \frac{\sum_{i \in (N_+^{\prime\alpha} \cap N_k')} S_i^k}{\hat{x}_k} + \frac{\sum_{i \in (N_-^{\prime\alpha} \cap N_k')} S_i^k}{\hat{x}_k} - \mu_k q_k \qquad k = 1,\ldots,K \tag{4.8}$$

$$\frac{1}{M} \sum_{i \in (N_-^{\prime\alpha} \cap N_k')} S_i^k \leq \mu_k \leq M \sum_{i \in (N_-^{\prime\alpha} \cap N_k')} S_i^k \qquad k = 1,\ldots,K \tag{4.9}$$

$$\begin{bmatrix} q_1 \\ \vdots \\ q_K \end{bmatrix} = \begin{bmatrix} a_{11}^* & \cdots & a_{1K}^* \\ \vdots & \ddots & \vdots \\ a_{K1}^* & \cdots & a_{KK}^* \end{bmatrix} \begin{bmatrix} q_1 \\ \vdots \\ q_K \end{bmatrix} + \begin{bmatrix} c_1^\star \\ \vdots \\ c_K^\star \end{bmatrix} \tag{4.10}$$

$$Q_R = \sum_{k=1}^{K} x_k q_k \tag{4.11}$$

$$\begin{aligned} & f_{ij}^{\prime k} \geq 0 \ \ \forall \, (i,j) \in L', k = 1,\ldots,K \\ & \mu_k \in \{0,1\}, \ k = 1,\ldots,K \end{aligned} \tag{4.12}$$

The formulation implements the idea of planning for adaptive capacity in a disrupted transportation network where the residual active network is presented by $G' = (N', L')$, with updated sets of links, L', and nodes, N'. The bundle constraint in Eq. (4.5) ties together the commodities by restricting the total flow of all the commodities on each link (i,j) to at most u_{ij}', the capacity of that particular link after disruption. $f_{ij}^{\prime k}$ represents the flow of commodity k across link (i,j) which remains in the updated set of links, L'. Eq. (4.6) represents mass balances on each node, where $b_i^{\prime k}$ captures demand/supply at each node in the residual network. A slack variable S_i^k is defined to capture undelivered commodities remaining with the suppliers, or unsatisfied demand at demand nodes. The magnitude of S_i^k is positive, and multiplier γ_i takes on a negative value for set of demand nodes (after disruption) N'_-, a positive value for supply nodes (after disruption) N'_+, and zero for transshipment nodes (after disruption) N'_0, as shown in Eq. (4.7). Eqs. (4.8)-(4.10) are constraints that translate remaining commodities at supply nodes and unsatisfied demand at demand nodes (in the geographical area of interest, α) into multi-industry inoperability. Here, $c_k^\star$ transfers remaining commodities of type k at the supplier and/or unsatisfied demands, S_i^k, into a final consumption reduction from Eq.(4.2) with respect to the total output of that particular commodity, representing the total output of industry k, $\hat{x}_k$. Considering N'_k as set of nodes related to industry k (in the residual network), which either supply or demand commodity k, in Eq. (4.8), q_k is added to capture the consequences of unsatisfied demand at nodes within the region on the inoperability of that industry, reasoning that any disruption leading to unsatisfied demands has an impact on the output of that particular industry which needs to be taken care of in the total interdependent inoperability. As the network might connect industries within the region of interest into their suppliers or customers out of the geographical area of interest, it is desired to consider the effect of failure in terms of remaining commodities at suppliers in the region of interest represented by $N_+^{\prime\alpha}$, and unmet demand at demand nodes within the region of interest represented by $N_-^{\prime\alpha}$. A binary coefficient, μ_k, in Eq. (4.8) takes on value 0 when there are no unsatisfied demands at demand nodes within the region under study and 1 when there is at least one demand node with unsatisfied needs. Eq. (4.9) requires that μ_k be binary, defining a sufficiently large M. Eq. (4.10) implements the IIM to capture the adverse effect of the disruption in terms of remaining commodities at supply nodes and unsatisfied demand at demand nodes. The multi-industry economic impacts of the failure devising a rerouting strategy are captured in Eq. (4.11) with total economic loss Q_R. And the objective function is the proportional economic saving, parametrized based on Eq. (4.3) in which Q_e, maximum economic loss experienced by the whole economy in the case of a disruption when no mitigating strategy is taken, is already calculated based on Section 4.2.1. and 4.2.2. The proposed approach benefits from the flexibility, scalability, and efficiency of the base MCNF paradigm with respect to optimization (Ahuja et al. 1993, Manfren 2012), as practiced in modeling interdependencies in critical infrastructure networks (e.g., Lee et al. (2007), Holden et al. (2013)).

4.3 Illustrative Example: Multi-Modal Freight Transport in Oklahoma and the Surrounding Region

A multi-modal freight transportation network, consisting of three important interstate highways, railways, and inland waterways that connect to the Mississippi River Navigation System via two ports, plays an important role in transporting commodities produced in the business economic areas within the state of Oklahoma to consumers in neighboring states. A portion of this multi-modal freight transportation network is illustrated on a case study, described in Section 2.4, to implement the proposed model to improve adaptive capacity with a post-disruption rerouting strategy. A scenario-based disruption defined as the removal of a particular network component is considered in the illustrative example. Customers in surrounding states are considered to be four combined demand nodes connecting to Oklahoma's multi-modal freight transportation network. The multi-industry impact of the disruption within the economy of the state of Oklahoma guides the rerouting of commodities throughout the residual network as an adaptive (short-term) strategy. The case study has been solved using optimization software LINGO, version 15.

4.3.1 Supply-Demand Network

Based on the combined estimated annual supply and demand in tons for the associated industries and states compiled from different databases (US Army Corps of Engineers 2013, Tulsa Port of Catoosa 2013, Bureau of Transportation Statistics 2010a,b, Port of Muskogee 2013, Bureau of Economic Analysis 2010), a list of monthly supply and demand is presented in Table 4.1 (assuming constant monthly demand, or annual demand divided by 12).

Table 4.1. Combined monthly demands/supplies at supply/demand nodes connecting through the network (in tons).

	Industry					
	311	324	325	327	333	339
Supply nodes in OK						
Oklahoma City	362526	0	300501	183188	23790	118242
Port of Catoosa	50244	454911	284685	25268	2470	424
Port of Muskogee	0	33962	0	31886	0	30021
Demand nodes outside of OK						
TX	97281	316905	204006	0	25838	30154
LA	50244	18449	0	0	267	0
AR	265245	153518	381180	41038	156	54494
IL	0	0	0	199304	0	64039

4.3.2 Freight Movement and Disruption

To parametrize the MCNF model, the cost vector is computed based on the transportation mode and the mileage of the distances between nodes: the per ton-mile for a barge is estimated at \$0.97, compared to \$2.53 for rail, and \$5.35 for trucking (Arkansas Waterway Commissions 2014). The monthly capacity of each link, shown in Table 4.2 in the appendix, is estimated from historical data as a shared constraint for all commodities flowing on the link (ODOT 2013), representing the availability of transportation facilities. Assuming that the total supply of commodity k is equal to the total demand of the same commodity throughout the network, as shown in Table 4.1, a baseline flow resulted in no remaining commodities at supply nodes and no unsatisfied demand at demand nodes when there is no disruption to the functionality of the network.

Table 4.2. Link capacities among the origin/destination nodes in the illustrative network (ODOT 2013).

Nodes	1	2	3	4	5	6	7	8	9	10	11
1				233333			241667		141667	516667	
2				15000	54167	62500	41667	283333		308333	112500
3				29583	15417	250833		24167			
4											
5											
6											
7											
8				316667			25000				
9				150000							141667
10						1000000					
11							133333		166667		

In the illustrative example, disruption scenarios are defined as the removal of a single network component at a time. It is assumed that a disruption, or the removal of a particular network component, lasts for a period of one month. Assuming that annual industry production accumulates consistently across the year (i.e., neither production nor interdependency relationships vary day-to-day, week-to-week, month-to-month), a smaller month-long time horizon is considered here as an appropriate proportion of a year to calculate the particular disruptive event cascading effect (e.g., a two-week closure of port facilities (Pant et al. 2011)). Shown in Table 4.3, three transshipment nodes within the state of Oklahoma, some segments of high volume-freight-traffic interstate highways, some segments of the North America Railroad, a local railroad which connects industrial parks to the North America Railroad, and parts of waterway system, were individually removed from the network to define the disruption scenarios. Focusing on the economy of the state of Oklahoma, and considering supply nodes within the state interacting with demand nodes in surrounding states, undelivered commodities remaining with suppliers or unsatisfied demand at demand nodes, as represented by S_i^k, affect industry output and result in propagated inoperability through many of the interconnected industries. In the illustrative example, all the supply nodes are within the state of Oklahoma and the four demand nodes are located outside of Oklahoma. Table 4.3 reports $\sum_{i \in (N_+'^{\alpha} \cap N_k')} S_i^k$, the sum of the slack (remaining supply) by commodity at the supply nodes when different network components are disrupted, omitting the flow on the disrupted component from the baseline flow within the network. As shown in Table 4.3, the *Petroleum and coal* industry (324) is directly vulnerable in all disruption scenarios except for the loss of link (1,7), while the *Food and beverage and tobacco* industry (311) would be affected only by the loss of link (2,5).

Table 4.3. Tons of remaining commodities at suppliers with the removal of network components.

Removed component	Sum of remaining commodities at supply nodes (tons)					
	311	324	325	327	333	339
Node 9	0	18960	91744	0	0	19740
Node 8	0	263776	0	17509	2048	0
Node 11	0	18960	71119	0	0	0
Link (1,7)	0	0	0	177628	0	64039
Link (9,11)	0	18960	71119	0	0	0
Link (2,5)	50244	3656	0	0	267	0
Link (8,4)	0	263776	0	0	2048	0
Link (2,8)	14793	157492	88627	0	0	0

4.3.3 Multi-industry Impact

As all the demand nodes are located outside of Oklahoma, failure in the form of the inability of suppliers to export commodities is modeled as a demand perturbation as calculated in Eq. (4.2). Other industries within the state will be affected by the interdependent effect of this failure, as captured by q^k, representing the extent to which an industry output will not be produced. And the effect of the disruption on the economy of the state is captured by Q, assuming that industries not using the transportation network have not experienced any demand perturbation.

Given the remaining commodities left at supply nodes, shown in Table 4.3, demand perturbation is calculated with Eq. (4.2). Resulting industry inoperability, q^k, is provided in Table 4 and depicted in Figure 4.3. The *Petroleum and coal* industry (324) is most vulnerable to the removal of the link (2,8), link (2,4), or node 8. The removal of these components also affect the operability of the *Nonmetallic minerals* industry (327), though to a lesser extent than the removal of link (1,7). The productivity of the *Chemical products* industry (325) is highly dependent on the connectivity of Tulsa and Oklahoma City through I-44, as represented by link (9,11), as well as transshipment nodes 9 and 11.

Table 4.4. Industry inoperability across six most important industries within the state of Oklahoma.

	Industry					
Removed component	311	324	325	327	333	339
Node 9	0.00E+00	9.00E-04	4.90E-03	0.00E+00	0.00E+00	1.50E-03
Node 8	0.00E+00	1.16E-02	9.00E-04	1.20E-03	1.60E-03	8.00E-04
Node 11	0.00E+00	9.00E-04	3.80E-03	0.00E+00	0.00E+00	1.00E-04
Link (1,7)	0.00E+00	1.00E-04	2.00E-04	8.90E-03	1.00E-04	4.50E-03
Link (9,11)	0.00E+00	9.00E-04	3.80E-03	0.00E+00	0.00E+00	1.00E-04
Link (2,5)	5.10E-03	2.00E-04	2.00E-04	1.00E-04	2.00E-04	2.00E-04
Link (8,4)	0.00E+00	1.16E-02	9.00E-04	3.00E-04	1.60E-03	8.00E-04
Link (2,8)	4.00E-04	1.16E-02	9.00E-04	1.20E-03	1.60E-03	8.00E-04

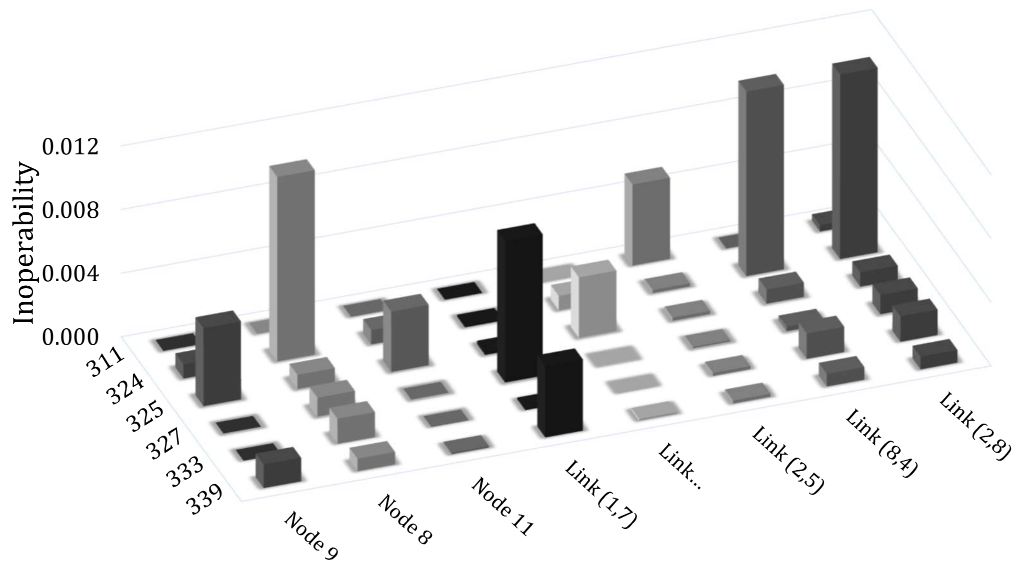


Figure 4.3. Graphical depiction of inoperability across six most important industries within the state of Oklahoma.

Considering each industry's production level in monetary value and calculating total impact of the disruption across the state's industries with *Q*, Table 4.5 and Figure 4.4 provide the supplementary analysis which elaborates the magnitude of loss (in million USD) experienced by different industries regarding the total economic loss. The interconnected nature of the industries within a region affect productivity of the other 56 industries operating in Oklahoma though individually to a much lesser extent than the six industries directly affected. Many industries are vulnerable to any sort of disruption affecting the operability of node 8, the intermodal terminal facilities at the Port of Catoosa, or either of the links connecting it to nodes 2 or 4, the port itself and the state of Texas, respectively. The *Petroleum and coal products* industry (324) is a high dollar industry in Oklahoma affected the most by the disruption scenarios, though less vulnerable to disruptions that remove links (2,5) or (1,7) from service.

Table 4.5. Economic losses across the six most important industries within the state of Oklahoma.

Removed component	Industry							Total multi-industry impact
	311	324	325	327	333	339	Others	
Node 9	0.12	11.04	6.67	0.09	0.20	14.77	17.59	50.47
Node 8	0.24	146.24	1.22	2.47	11.90	7.95	159.32	329.33
Node 11	0.04	10.80	5.16	0.06	0.11	0.78	12.82	29.79
Link (1,7)	0.23	0.92	0.23	18.17	0.37	45.79	22.41	88.12
Link (9,11)	0.04	10.80	5.16	0.06	0.11	0.78	12.82	29.79
Link (2,5)	28.04	2.70	0.26	0.25	1.65	2.40	23.64	58.95
Link (8,4)	0.24	146.20	1.21	0.69	11.88	7.88	158.46	326.56
Link (2,8)	2.12	146.29	1.24	2.48	11.91	8.10	160.71	332.84

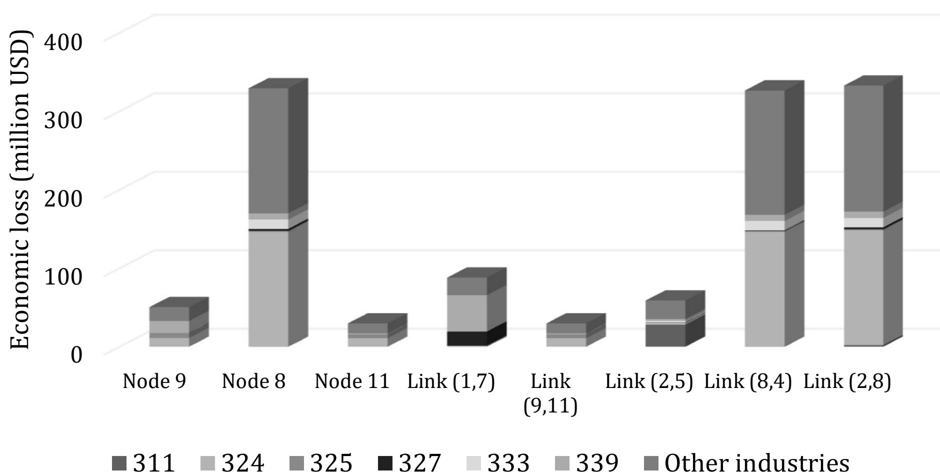


Figure 4.4. Interdependent economic losses in Oklahoma due to network component removal.

4.3.4 Planning for Adaptive Capacity

During the month-long period of disruption, the efficacy of contingency rerouting through the residual network is determined according to its reduction in economic productivity of Oklahoma. Respectively, Table 6 and Table 7 report interdependent economic inoperability experienced by the six most important industries in Oklahoma and the consequential multi-industry economic losses following the contingency rerouting strategy devised from the model developed in Eqs. (4.4)-(4.12) to minimize $Я_e^R$. $Я_e^R$ is defined as a measure to lessen the maximum potential drop in the regional economy, lies on (0,1), where $Я_e^R = 0$ means that under a disruption scenario e, there is no way to avoid the maximum possible loss in the economy of the region by rerouting the supply-demand network, and $\eta_p = 1$ means that under a disruption scenario e, it is possible to maintain the full productivity of the regional economy by rerouting commodity flows through the residual network. Comparing the inoperability caused by the removal of the network component with and without devising a contingent rerouting strategy during the period of disruption, shown in Figure 5 and Figure 6 respectively, shows that the proposed model to plan for adaptive capacity tries to facilitate the trades in high dollar industries like *Petroleum and coal products* (324) and *Miscellaneous manufacturing* (339), while having less impact on *Chemical products* (325) or *Food and beverage and tobacco* (311) industries.

Table 4.6. Economic inoperability caused by the disruption after devising a contingent rerouting strategy.

Removed component	Industry					
	311	324	325	327	333	339
Node 9	2.00E-04	0.00E+00	4.80E-03	0.00E+00	0.00E+00	0.00E+00
Node 8	1.10E-03	7.20E-03	5.00E-03	8.00E-04	1.00E-04	5.00E-04
Node 11	2.00E-04	0.00E+00	4.70E-03	0.00E+00	0.00E+00	0.00E+00
Link (1,7)	0.00E+00	0.00E+00	1.00E-04	7.50E-03	0.00E+00	1.00E-04
Link (9,11)	2.00E-04	0.00E+00	3.60E-03	0.00E+00	0.00E+00	0.00E+00
Link (2,5)	0.00E+00	1.00E-04	1.50E-03	0.00E+00	2.00E-04	0.00E+00
Link (8,4)	1.10E-03	7.20E-03	5.00E-03	2.00E-04	1.00E-04	5.00E-04
Link (2,8)	1.50E-03	7.00E-03	5.20E-03	2.00E-04	1.00E-04	5.00E-04

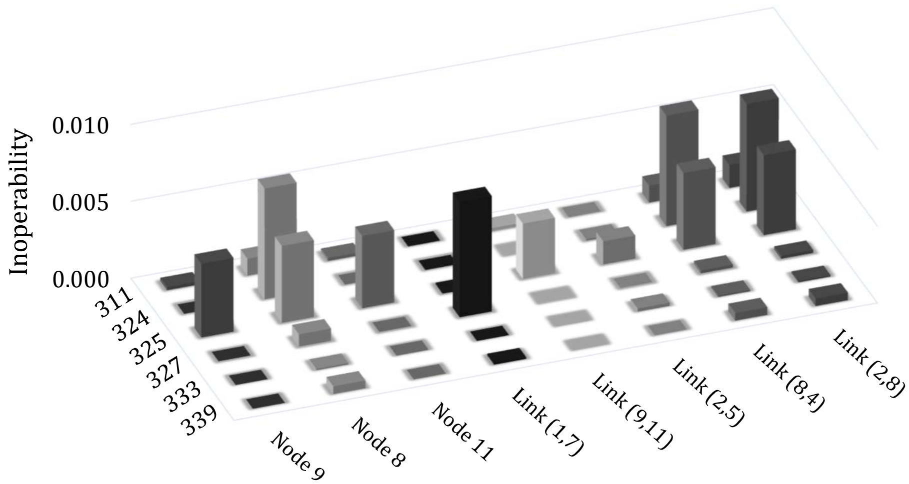


Figure 4.5. Economic inoperability caused by the disruption devising a contingent rerouting.

Figure 5 depicts how contingent rerouting would affect the maximum loss across multiple Oklahoma industries following the removal of the particular components. And, as listed in Table 4.7, this strategy could lessen the vulnerability of the whole system with respect to the removal of particular components like link (2,5) as part of the inland waterway network. It is also inferred that industries in Oklahoma are most vulnerable to disruptions that cause inoperability in (i) node 8, the intermodal terminal facilitates the movement of commodities in the industrial park of Port of Catoosa to out-of-state customers, (ii) link (8,4), a portion of railroad that connects Oklahoma to Texas City, TX, or (iii) link (2,8), a local railroad that connects the Port of Catoosa to the North America railroad intermodal terminal, as even rerouting cannot sufficiently enhance the performance the collective industries, as measured by $Я_e^R$, by more than 36%. As shown in Table 7, the maximum possible loss resulting from the removal of a network component will be avoided with a contingent rerouting strategy, as in some cases system performance improved up to 85%.

Table 4.7. Economic losses, in million USD, within the state of Oklahoma after planning for adaptive capacity.

Removed component	Industry							Total multi-industry impact	$Я_e^R$
	311	324	325	327	333	339	Others		
Node 9	0.85	0.41	6.57	0.03	0.05	0.42	3.00	11.32	0.78
Node 8	5.98	90.15	6.80	1.66	0.78	5.17	100.68	211.22	0.36
Node 11	0.85	0.40	6.34	0.03	0.05	0.41	2.92	10.98	0.63
Link (1,7)	0.02	0.37	0.11	15.26	0.10	0.58	7.33	23.78	0.73
Link (9,11)	0.84	0.31	4.83	0.02	0.04	0.32	2.36	8.72	0.71
Link (2,5)	0.02	1.82	2.06	0.02	1.43	0.30	3.28	8.92	0.85
Link (8,4)	5.98	90.12	6.79	0.44	0.78	5.12	100.10	209.33	0.36
Link (2,8)	8.42	87.77	7.09	0.45	0.78	5.21	99.48	209.22	0.37

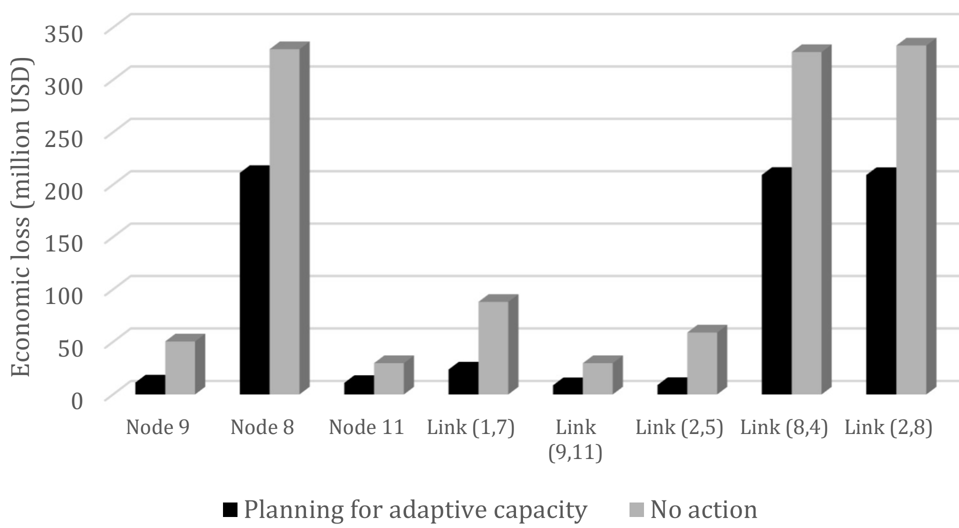


Figure 4.6. Total economic loss across all industries in Oklahoma, contingent rerouting versus no action.

As a contingent rerouting strategy is sought considering the total economic impact embedded in Eq. (4.3) , priorities given to high-dollar industries and those with the highest interdependent impacts across industries. Though Figure 4.6 shows the absolute benefit of implementing the adaptive capacity planning strategy in the case of different disruption scenarios, there might be cases in which the rerouting strategy results in losses to particular industries. Figure 4.7 shows how contingent rerouting strategies affect different industries (in the form of box plots generated across the eight disruption scenarios). For example, the rerouting strategies taken following the eight different disruption scenarios would lessen the economic loss in *Petroleum and coal products* (324) industries by \$25.46 million, on average, and at least \$0.55 million, in the case of losing link (1,7). Overall, the *Chemical products* (325) and *Food and beverage and tobacco* (311) industries are most adversely impacted, as shown in Figure 4.7, because optimal contingency rerouting tends not to benefit these industries in favor of the larger economy, as shown in Figure 4.6.

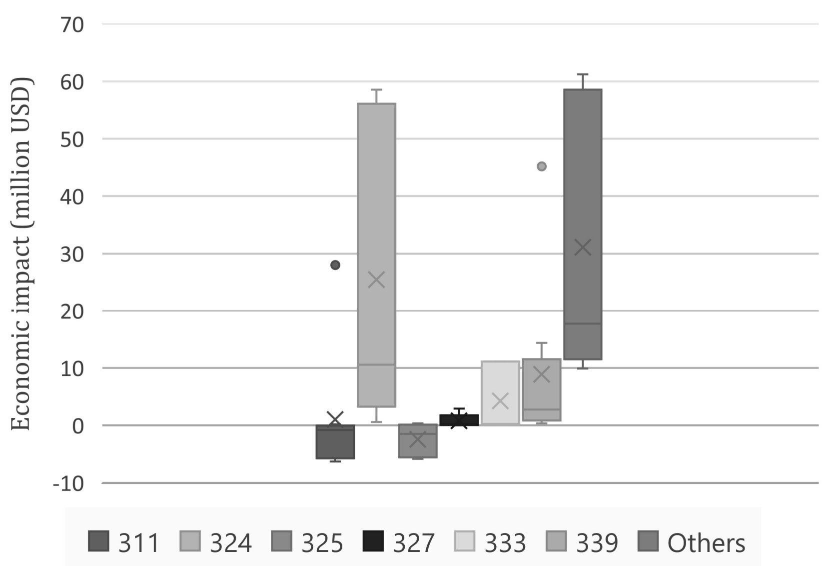


Figure 4.7. Effects of contingent rerouting on different industries.

4.3 Concluding Remarks

With regard to the three components of resilience capacity identified by Vugrin et al. (2011), most freight transportation network resilience studies focus on pre-disruption prevention investments via absorptive capacity or post-disaster network restoration strategies via restorative capacity. And such is typically done by defining system performance as a measure related to the serviceability of the system (e.g., travel time/distance, flow, throughput) or a topological measure related to the network structure (e.g. centrality, connectivity, betweenness). This work, however, emphasizes adaptive capacity in the form of contingent rerouting strategies to manage the supply-demand network after a disruptive event to lessen the total economic impact.

More specifically, this work proposes an optimization formulation to accommodate the flow through the residual network and maintain the productivity of the economy of the desired region by (i) integrating a multi-commodity network flow model, representing a multi-modal freight transportation network, with a risk-based economic interdependency model, to capture the propagation of the failure in a group of interconnected industries, and (ii) defining a measure of adaptive capacity to valuate rerouting strategies. The formulation provides a means to consider the final role of a freight transportation network as the facilitator within the economy in planning for adaptive capacity after a disruption.

Part of a multi-modal freight transportation network connecting Oklahoma to surrounding states has been considered to develop a stylized case study in which supply nodes are located in the state of Oklahoma and demand nodes are located in surrounding states. We address the efficacy of implementing the adaptive capacity planning formulation in Oklahoma when a scenario-based disruption disables a particular network component for a month. Results suggest a successful avoidance of maximum potential loss in high dollar industries such as *Petroleum and coal products* (324) and *Miscellaneous manufacturing* (339), and a consequent static resilience in the economy of the state, as the average maximum loss could be avoided by more than 50%. Though a proportion of the total economic impact has been considered to seek adaptive planning strategies in this study, further work should embed larger social and community impacts in the problem formulation.

This initial formulation can be further improved by accounting for the real-world intermodal container planning considerations and other dynamic issues. Complementary models to plan for system resilience as a function of absorptive and restorative capacity, as well as the adaptive capacity-focused formulation proposed here, could more effectively highlight the tradeoffs among different resilience capacity planning perspectives.

CHAPTER 5

PLANNING FOR RESTORATIVE CAPACITY

5.1 Introduction

This work focuses on enhancing network resilience via restorative capacity. Most work in infrastructure network recovery focuses on the restoration process as an effort to minimize unsatisfied demands in each time period. Nurre et al. (2012) introduce a design and scheduling formulation that maximizes the total weighted flow reaching to demand nodes in each time period of the recovery horizon. Miller-Hooks et al. (2012) propose restoring disrupted network performance as a function of satisfied demand in each time period of the restoration horizon from the perspective of network resilience. Sharkey et al. (2015) expand the model by Nurre et al. (2012) to recover interdependent infrastructure networks. In terms of optimizing network connectivity, Aksu and Ozdamar (2014) formulate a multi-vehicle problem to recover blocked links that are critical for maintaining network connectivity under limited recovery resources. Celik et al. (2015) also plan debris cleaning processes with the aim of recovering transportation network connectivity under uncertain nature of the problem. Kasaei and Salman (2016) propose an arc routing problem that reconnects network components within a recovery time horizon.

Acknowledging that infrastructure networks do not exist for their own sake but serve society, particularly as a means to promote economic productivity, this work expands upon the recent literature in optimizing infrastructure network recovery via demand satisfaction or network connectivity to accounting for multi-industry economic impacts. We focus on measuring the effectiveness of restorative capacity on economic productivity with the proportional value of the maximum loss that can be avoided by recovery decisions, adapted from Rose (2004). This is depicted graphically in Figure 5.1 and mathematically in Eq. (5.1), where $\%\Delta DY$ represents the economic loss given that some recovery action is taken and $\%\Delta DY^{max}$ represents the maximum economic loss due to the disruption while no action is taken. This quantitative approach is used in this study to define a performance measure for the system's ability to restore its functionality ($\%\Delta DY^{max} - \%\Delta D$) after a disruptive. In this work $\%\Delta DY$ and $\%\Delta DY^{max}$ refer to changes in total output produced in an economy of interconnected industries. In this sense, these measures are analogous to the concept of inoperability, a well-studied topic in the literature of interdependent industries and infrastructures (Santos and Haimes 2004, Barker and Haimes 2009, Barker and Santos 2010a,b). Inoperability, q, quantifies the proportional extent to which a system (e.g., economic system) is not functioning in an as-planned manner, thereby providing a metric to describe the behavior of a system regardless of the measure describing its proper function (e.g., flow capacity, connectivity, production output). As further discussed in Section 5.3., this measure of restorative capacity is extended to represent maximum loss that is avoided in each time period by devising recovery actions till the full system restoration.

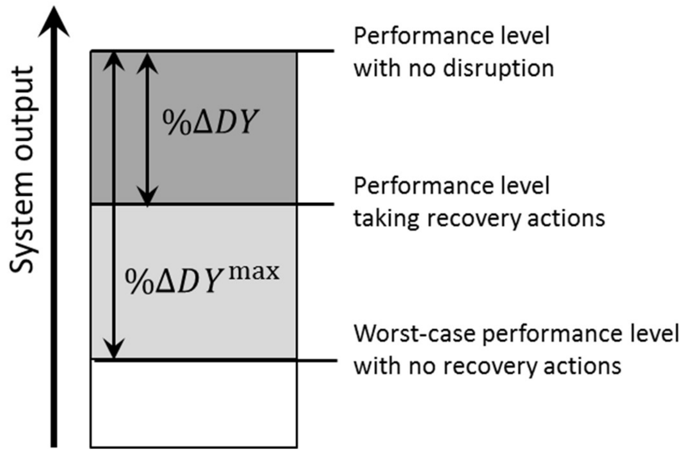


Figure 5.1. The performance components of restorative capacity (adapted from Pant et al. (2014)).

$$restorative\ capacity = \frac{\%\Delta DY^{max} - \%\Delta DY}{\%\Delta DY^{max}} \quad (5.1)$$

5.2 Modeling Freight Network Restoration

A multi-modal freight transportation network can be considered a facilitator of economic productivity as it enables the flow of commodities among industries located in multiple regions. Following a disruptive event, obstacles in commodity movement ripples throughout the interconnected industries, as input to one industry may be disrupted output from another industry, thus affecting the entire (regional) economy. As such, we seek recovery decisions that enable economic productivity across multiple industries. We propose an optimization framework to devise recovery decision by integrating (i) a multi-commodity network flow model of freight movement, (ii) a risk-based interdependency model of multi-regional, multi-industry impacts, and (iii) an objective function that addresses restorative capacity with a measure of economic resilience (Rose 2004, 2009, 2013, Pant et al. 2014). The proposed optimization model is developed following a three-step approach, as illustrated in Figure 5.2.

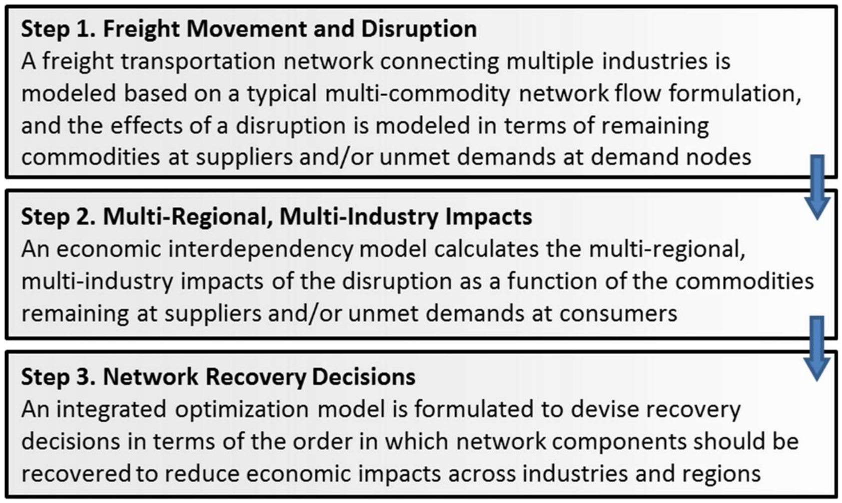


Figure 5.2. Three-step approach to devise network recovery with multi-regional, multi-industry impacts.

5.2.1 Freight Movement and Disruption

A typical MCNF model is used to represent a network of industries located in multiple regions. And, a scenario-based removal of network components known as interdiction (Murray et al. 2008) is a common theme in modeling and analysis of supply-demand network disruption. Interdiction analyses encompass a wide range of possible disruptions that may vary with respect to spatial scales, correlation of disruptive events, sequence of failures, and event duration. In the case of any disruption modeled as the removal of a network component or a set of components (or a drop in the functionality of the network modeled as reduction of link capacities), the consequences are calculated by deducting the commodity flows on the affected links from the baseline flow. Slack variable $S_{it}^{k'}$ reflects the quantity of commodity k' at node i at time t that is either (i) undelivered and remaining with the suppliers or (ii) unsatisfied demand experienced by consumers. This slack variable will be used subsequently to drive the calculation of inoperability among multiple industries.

5.2.2 Multi-Regional, Multi-Industry Economic Impact

To model the interdependent adverse effect of commodity flow disruption on multiple industry sectors located in different regions, we use a multi-regional extension of Inoperability Input-Output Model (IIM). The IIM is an extension of the traditional economic input-output model (Leontief 1986), a linear model of the commodity flows in a set of interconnected industries. This section provides methodological background on the risk-based multi-regional interdependency model used to measure the economic impacts of a transportation disruption in terms of remaining commodities at suppliers and unmet demands at demand nodes.

Input-output model and its multi-regional extension: the traditional I-O model has been extended to represent multi-regional economic interdependency (Miller and Blair 2009). A regional input-output matrix $\mathbf{A}^r$ is developed by modifying the elements of the **A** matrix. As shown in Eq. (5.2), l_k^r, referred to as a location quotient, is defined to indicate how well industry k's production satisfies the regional demand.

$$a_{kh}^r \begin{cases} l_k^r a_{kh}, & l_k^r < 1 \\ a_{kh}, & l_k^r \geq 1 \end{cases} \tag{5.2}$$

The location quotient, l_k^r, is mathematically defined in Eq. (5.3), where x_k^r is the output of industry k in region r, x_{total}^r is the output of all industries in region r, x_k is the output of industry k at the national level, and x_{total} is the output of all industries at the national level.

$$l_k^r = \frac{x_k^r / x_{total}^r}{x_k / x_{total}} \tag{5.3}$$

As discussed by Isard et al. (1998), in multi-regional analysis, it is desired to consider the effects of interdependencies due to the exchange of goods and services between regions. The authors extended the input-output model to incorporate inter-regional commodity exchanges by defining an inter-regional relationship as $z_{kh}^{rr'} = z_k^{rr'} z_h^{r'}$, where $z_{kh}^{rr'}$ is the amount of output of industry k in region r that is used by industry h in region r', $z_k^{rr'}$ is the amount of output of industry k that goes from region r to r', and $z_h^{r'}$ is the amount of output of industry h coming from all regions into r' that is used as input by industry h. Isard et al. argued that $z_k^{rr'}$ is proportional to $\xi_k^{r'}$, the total amount of commodities related to industry k that come into region r' from all other regions (i.e., $z_k^{rr'} = \psi_k^{rr'} \xi_k^{r'}$). Also, $z_{kh}^{r'}$ is proportional to the output of the industry h in region r' (i.e., $z_{kh}^{rr'} = a_{kh}^{r'} x_h^{r'}$). Hence, the inter-regional technical coefficient is defined with Eq. (5.4).

$$a_{kh}^{rr'} = \frac{z_k^{rr'} z_{kh}^{r'}}{\xi_k^{r'} x_h^{r'}} = \psi_k^{rr'} a_{kh}^{r'} \tag{5.4}$$

Ultimately, an inter-regional input-output model is proposed in Eq. (5.5), the details of which can be found in Isard et al. (1998) and Miller and Blair (2009).

$$x_k^r = \sum_{r'=1}^{R} \sum_{h=1}^{K} \psi_k^{rr'} a_{kh}^{r'} x_h^{r'} + \sum_{r'=1}^{R} \psi_k^{rr'} c_k^r \tag{5.5}$$

The multi-regional, multi-industry input-output model is provided in Eq. (5.6). Each sub-matrix $\boldsymbol{\Psi}^{rr'}$ is a $K \times K$ diagonal matrix whose diagonal elements are the proportions of all commodities $\psi_k^{rr'}$, $\forall\, k \in \{1, \dots, K\}$ that originated in region r and are consumed in region r'. Each sub-matrix $\boldsymbol{\Psi}^{11}$, referred to as the trade coefficient matrix, are parametrized using the Commodity Flow Survey database that documents the annual flow of goods in US dollars using multi-modal transportation across different regions in the United States, collected by the Bureau of Transportation Statistics (2010).

$$\begin{bmatrix} x^1 \\ \vdots \\ x^R \end{bmatrix} = \begin{bmatrix} \Psi^{11} & \cdots & \Psi^{1R} \\ \vdots & \ddots & \vdots \\ \Psi^{R1} & \cdots & \Psi^{RR} \end{bmatrix} \begin{bmatrix} A^1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & A^R \end{bmatrix} \begin{bmatrix} x^1 \\ \vdots \\ x^R \end{bmatrix} + \begin{bmatrix} \Psi^{11} & \cdots & \Psi^{1R} \\ \vdots & \ddots & \vdots \\ \Psi^{R1} & \cdots & \Psi^{RR} \end{bmatrix} \begin{bmatrix} c^1 \\ \vdots \\ c^R \end{bmatrix} \tag{5.6}$$

Inoperability Input-Output Model and its multi-regional extension: Crowther and Haimes (2010) followed the same principles in developing multi-regional input-output model to propose the Multi-Regional Inoperability Input-Output Model (MRIIM) by integrating Eqs. (5.6) and (2.3). In the MRIIM, provided in Eq. (5.7), each of the $K \times K$ sub-matrices $\boldsymbol{\Psi}^{\star rr'}$, $\forall\, r, r' \in \{1,2, \dots, R\}$ is normalized by the diagonal regional output matrices $\mathrm{diag}(x^r)$, $\forall\, r \in \{1,2, \dots, R\}$.

$$\begin{aligned} \begin{bmatrix} \mathbf{q}^1 \\ \vdots \\ \mathbf{q}^R \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Psi}^{\star 11} & \cdots & \boldsymbol{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Psi}^{\star R1} & \cdots & \boldsymbol{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{A}^{\star 1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{A}^{\star R} \end{bmatrix} \begin{bmatrix} \mathbf{q}^1 \\ \vdots \\ \mathbf{q}^R \end{bmatrix} \\ + \begin{bmatrix} \boldsymbol{\Psi}^{\star 11} & \cdots & \boldsymbol{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Psi}^{\star R1} & \cdots & \boldsymbol{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{c}^{\star 1} \\ \vdots \\ \mathbf{c}^{\star R} \end{bmatrix} \end{aligned} \tag{5.7}$$

Total economic losses, the combination of direct and indirect losses, can be calculated by multiplying each industry's production level by its inoperability level: for industry k, $Q_k = x_k q_k$, or for the entire economy of industries, $Q = \mathbf{x}^T \mathbf{q}$. A multi-regional extension of these calculations can measure the total economic loss in the region under study. As such, planning decisions can be made with respect to some combination of inoperability or economic impact at the industry level, the multi-industry level, or for different regions.

MRIIM Application to Freight Disruption: following a disruption in freight transportation infrastructure, commodity movement is assumed to be degraded and the whole system of interconnected industries is faced with a failure in the form of remaining commodities at suppliers and unmet demands at consumers. The propagation of the failure throughout interconnected industries located in multiple region is formulated using MRIIM. Santos and Haimes (2004) proposed a demand-reduction IIM that has been successfully employed to study multi-industry impacts of perturbations in supply and demand (e.g., Resurreccion and Santos (2013), Pant et al. (2011), Haggerty et al. (2008), Lian and Haimes (2006)). Here, the failure is translated into the two IIM metrics of inoperability and final consumption perturbation based on a demand-reduction MRIIM implemented by Pant et al. (2011) in modeling supply and demand perturbation caused by an inland waterway port closure. In the proposed approach, the remaining commodities at suppliers after a disruption are considered as final consumption perturbations. And the effects of the failure at demand nodes in the form of unmet demands is modeled as a “forced” demand reduction, assuming that a disruption decreases the supply of a commodity for a demand node while the final external consumption remains virtually unaffected. In such a case, the demand nodes temporarily sacrifice their internal need for that commodity until it returns to its as-planned supply level, and a surrogate for supply reduction is calculated from the combination of “forced” internal consumption and an output inoperability.

Modeling Remaining Supply: the remaining commodities at a supplier of commodity k located in node i at region r will be considered as a reduction in final consumption. Final consumption for industry k includes commodities consumed by industry k itself internally, or $(\hat{c}_k^r)_{\text{int}}$, and the amount of external consumption that is exported through the network G, or $(\hat{c}_k^r)_G$, as modeled in Eq. (5.8). It is assumed that the disruption results in losses of commodity flows only through the network, so industry production activities unrelated to the network experience no direct failure though might be affected indirectly due to an interdependent loss of economic productivity. When a disruption causes difficulties for industry k in region *r* only in exporting commodities, it experiences commodities remaining at supply nodes in region *r* totaling $\sum_{i\,\in(\,N_+^r \cap N_k)} S_i^k$, where N_+^r represents the set of nodes that are home to suppliers in region r. This is shown in Eq. (5.9). As such, the final consumption perturbation for industries that experience difficulties only in exporting commodities is modeled as the amount of slack divided by as-planned industry output in Eq. (5.10).

$$\hat{c}_k^r = (\hat{c}_k^r)_{\text{int}} + (\hat{c}_k^r)_G \qquad k \in \{1, \dots, K\} \tag{5.8}$$

$$\hat{c}_k^r - \tilde{c}_k^r = \sum_{i\,\in(\,N_+^r \cap N_k)} S_i^k \qquad k \in \{1, \dots, K\} \tag{5.9}$$

$$c_k^{\star r} = \frac{\sum_{i\,\in(\,N_+^r \cap N_k)} S_i^k}{\hat{x}_k^r} \qquad k \in \{1, \dots, K\} \tag{5.10}$$

Modeling Unmet Demand: as discussed by Pant et al. (2011), the amount of import (input) of industry k at demand nodes in region r, defined as $\sum_{i\,\in(N_-^r \cap N_k)} -b_i^k$, contributes toward the production activity and the internal consumption of industry k at region r. Thus, when a disruption causes difficulties for industry k at region r in importing commodities, it experiences unmet demands totaling $\sum_{i \in (N^{r}_{-} \cap N_k)} S_i^k$. The consequences are the loss of output, $\Delta\hat{x}_k^r = \hat{x}_k^r - \tilde{x}_k^r$, and final internal consumption, $\Delta(\hat{c}_k)_{\text{int}}$.

$$\sum_{i \in (N^{r}_{-} \cap N_k)} S_i^k = \Delta\hat{x}_k^r + \Delta(\hat{c}_k^r)_{int} \qquad k \in \{1, \dots, K\} \tag{5.11}$$

Therefore, for industry k, unmet demand causes an inoperability, q_k, measured as the loss of production in industry k as a proportion of its original production level, with $\Delta\hat{x}_k/\hat{x}_k$. Also, a disruption in internal consumption, as shown in Eq. (5.8), causes a final consumption perturbation, $c_k^\star$, and is modeled as a measure of the change in the final consumption as a proportion of the original production level in industry k, with $\Delta\hat{c}_k/\hat{x}_k$. The failure in the form of unmet demand is formulated following an approach adapted from the port disruption work of Pant et al. (2011, 2015) and the transportation network vulnerability formulation of Darayi et al. (2017), in which a slack variable S_i^k is defined to capture unsatisfied demand at demand nodes (or undelivered commodities remaining with the suppliers), shown in Eq. (5.12). For the industries experiencing difficulties only in importing their required commodities, there exists a final consumption perturbation, as modeled in Eq. (5.13).

$$\frac{\Delta\hat{c}_k^r}{\hat{x}_k^r} = \frac{\sum_{i \in (N^{r}_{-} \cap N_k)} S_i^k - \Delta\hat{x}_k^r}{\hat{x}_k^r} \qquad k \in \{1, \dots, K\} \tag{5.12}$$

$$c_k^{\star r} = \frac{\sum_{i \in (N_-^r \cap N_k)} S_i^k}{\hat{x}_k^r} - q_k^r \qquad k \in \{1, \dots, K\} \tag{5.13}$$

To quantify the inoperability and final consumption perturbations for the collection of K interconnected industries located in R regions, a complete solvable system of Eqs. (5.10) and (5.13) combined with the MRIIM in Eq. (5.7) is implemented. While in actual situations, some industries would likely consist of both supply and demand nodes in each region, Eqs. (5.10) and (5.13) capture failure in either *only* supply nodes or *only* demand nodes within a particular industry at a region. Eq. (5.14) formulates the total final consumption perturbation for industry k in the case of having both exporting (supply) and importing (demand) roles.

$$c_k^{\star r} = \frac{\sum_{i \in (N_+^r \cap N_k)} S_i^k}{\hat{x}_k^r} + \frac{\sum_{i \in (N_-^r \cap N_k)} S_i^k}{\hat{x}_k^r} - q_k^r \qquad k \in \{1, \dots, K\} \tag{5.14}$$

As a result, the perturbation vector for region r ($\mathbf{c}^{\star r}$), whose elements are captured by Eqs. (5.10), (5.13), or (5.14) depending on the importing/exporting role the nodes belonging to each industry in each region, parameterizes the interdependency model in Eq. (5.7). And, consequently, regional vector of inoperability $\mathbf{q}^r$ consisting of K elements of inoperability for each industry in region r can be calculated. Following a disruptive event that causes difficulties for freight movement (and results in remaining commodities at suppliers and unmet demands), q_k^r measures the proportional extent to which as-planned productivity or functionality is not realized in industry k at region r. Considering each industry's production level in monetary value and calculating the total impact of the disruption across the regions. These multi-regional, multi-industry analyses gives us an opportunity to plan for network restoration considering economic impacts, as discussed in the next step.

5.2.3 Step 3: Planning for Restorative Capacity

When a disruption leads to the loss of multiple network components, regional economies and multiple industries that relied on the functionality of the network experience inoperability and economic losses. We desire to tackle recovery actions in terms of restoration failed network components with multi-industry economic productivity in mind. Restorative capacity is considered to be the extent to which a freight transportation network is capable of being recovered through the assignment of work crews. Based on the static measure of restorative capacity modeled in Eq. (5.1), a time-based formulation is proposed in Eq. (5.15) that captures the proportional economic loss (considering maximum loss in case of no recovery action) that could be avoided at time period t by the set of recovery actions devised up to t. $Q_{\max}$ represents the summation of economic loss in multiple industries located in multiple regions following a disruption, and Q_t is the economic loss at time t considering the proportionally recovered network in the meantime. Recall that economic loss for industry k at region r is calculated by multiplying the proportional inoperability, q_k^r found using Eq. (5.7), by the expected production level in monetary units, or $Q_k^r = x_k^r q_k^r$. Total economic losses at each time period is a summation of Q_k^r over multiple industries in multiple regions for that particular period of time. Recovery decisions are made to maximize restorative capacity over multiple time periods, formulated in Eq. (5.15).

$$Я_t = \frac{Q_{max} - Q_t}{Q_{max}} \tag{5.15}$$

A regional restorative capacity measure is proposed in Eq. (5.16) represents the economic productivity improvement in region r triggered by restorative decisions up to time t. Likewise, an industry-specific measure of restorative capacity at time t is formulated in Eq. (5.17).

$$Я_t^r = \frac{Q_{max}^r - Q_t^r}{Q_{max}^k} \tag{5.16}$$

$$Я_{k,t}^r = \frac{Q_{k,max}^r - Q_{k,t}^r}{Q_{k,max}^r} \tag{5.17}$$

Each node in the transportation network can play the role of a supplier and a demand node simultaneously. We do note that no supplier in a region is permitted to satisfy demand nodes in that region. To implement that in the model, we connect two separated supply and demand dummy nodes to each non-transshipment node with the same amount of supply and demand as those amounts which are included in that particular node. Note that this expansion on the network turns the non-transition nodes to a transition node. We also assume that each industry includes two types of commodities and no region supplies a commodity that is also demanded in that region. Notation employed in the problem formulation is summarized as follows:

Sets and indices	
N	Set of nodes
L	Set of links
N_+	Set of supply nodes
N_-	Set of demand nodes
N_0	Set of transshipment nodes
N'	Set of disrupted nodes
L'	Set of disrupted links
$t = 1, \dots, T$	Index of discrete time periods, where T is the end of the time horizon
$k = 1, \dots, K$	Index of industries, where K is the total number of industries

α^k	Set of commodities belonging to industry k
N_+^k	Set of supply nodes in industry k
N_-^k	Set of demand nodes in industry k
$k' = 1, \dots, K'$	Index of types of commodities in each industry, where K' is the total number of commodities, each industry is made up of two different types of commodities
$N_+^{k'}$	Set of supply nodes in commodity k' of industry k
$N_-^{k'}$	Set of demand nodes in commodity k' of industry k
$r = 1, \dots, R$	Index of regions, where R is the total number of regions
N_+^r	Set of supply nodes in the region r
N_-^r	Set of demand nodes in the region r
Parameters	
u_{ij}	Capacity of link (i,j) before disruption
π_i^k	Total production of industry k in node i
$b_i^{k'}$	Mass-balance parameter representing supply/ demand/transshipment of commodity k' at node i after disruption. For supply nodes $b_i^{k'} > 0$, for demand nodes $b_i^{k'} < 0$, and for transshipment nodes $b_i^{k'} = 0$
x_r^k	Production level of industry k in region r in monetary value
$T^{*(k\times r)}$	Element of the normalized multi-regional interdependency matrix T^* of size $(K\times R)\times(K\times R)$
$\gamma_{it}^{k'}$	Multiplier of the slack term to represent slack at supply nodes ($\gamma_{it}^{k'} = 1, \forall i \in N_+^{k'}$), demand nodes ($\gamma_{it}^{k'} = -1, \forall i \in N_-^{k'}$), and transshipment nodes ($\gamma_{it}^{k'} = 0, \forall i \in N_=^{k'}$)
Decision variables	
$f_{ijt}^{k'}$	Integer variable representing the flow of commodity k' of industry k across link (i,j) at time t after a disruptive event
$S_{it}^{k'}$	Integer slack variable representing undelivered commodity k' of industry k remaining with the supply node i at time t or unsatisfied demand of commodity k' of industry k at demand node i at time t
μ_{ijt}	Binary variable equal to 1 when the restoration process of disrupted link (i,j) finishes at time t, and 0 otherwise
β_{ijt}	Binary variable equal to 1 when link (i,j) is operational at time t, and 0 otherwise
ω_{kt}^r	Binary variable equal to 1 if there exists any unsatisfied demand of commodities in industry k in region r at time t, and 0 otherwise
${c^*}_{rt}^k$	Continuous variable representing final consumption perturbation for industry k in region r at time t
q_{rt}^k	Continuous variable representing inoperability level of industry k in region r at time t
Q_{rt}^k	Continuous variable representing total economic loss of industry k in region r at time t

Planning for restorative capacity by recovering the disrupted links in an order which leads to the minimum total economic loss over the time horizon is formulated as follows.

$max \sum_{t=1}^{T} Я_t$	(5.18)
$\sum_{k=1}^{K'} f_{ijt}^{k'} \leq u_{ij}, \quad \forall\, (i,j) \in L, t = 1, \dots, T$	(5.19)
$\sum_{k'=1}^{K'} f_{ijt}^{k\prime} \leq \beta_{ijt} u_{ij}, \quad \forall\, (i,j) \in L', t = 1, \dots, T$	(5.20)
$\sum_{(i,j)\in L} f_{ijt}^{k'} - \sum_{(j,i)\in L} f_{jit}^{k'} + \gamma_{it}^{k'} S_{it}^{k'} = b_i^{k'}, \quad k' = 1, \dots, K', t = 1, \dots, T$	(5.21)
$\sum_{t=1}^{T} \mu_{ijt} \leq 1\,, \quad \forall\, (i,j) \in L'$	(5.22)
$\beta_{ijt} \leq \sum_{s=1}^{t} \mu_{ijs}\,, \quad \forall\, (i,j) \in L', t = 1, \dots, T$	(5.23)
$c^{*k}_{rt} = \frac{\sum_{k'\in N_+^{k'}} \sum_{i\,\in(\,N_+^r \cap N_k)} S_{it}^{k'}}{\hat{x}_k^r} + \frac{\sum_{k'\in N_-^{k'}} \sum_{i\,\in(\,N_-^r \cap N_k)} S_{it}^{k'}}{\hat{x}_k^r} - \omega_{kt}^r q_{kt}^r,$ $r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T$	(5.24)
$\frac{1}{\hat{x}_k^r} \sum_{k'\in\alpha^k} \sum_{i\in N_+^r} S_{it}^{k'} \leq \omega_{kt}^r \leq \hat{x}_k^r \sum_{k'\in\alpha^k} \sum_{i\in N_+^r} S_{it}^{k'}\,, r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T$	(5.25)
$Q_{rt}^k = x_r^k q_{rt}^k, \quad r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T$	(5.26)
$\begin{bmatrix} \boldsymbol{q}_t^1 \\ \vdots \\ \boldsymbol{q}_t^R \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Psi}^{\star 11} & \cdots & \boldsymbol{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Psi}^{\star R1} & \cdots & \boldsymbol{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \boldsymbol{A}^{\star 1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{A}^{\star R} \end{bmatrix} \begin{bmatrix} \boldsymbol{q}_t^1 \\ \vdots \\ \boldsymbol{q}_t^R \end{bmatrix} + \begin{bmatrix} \boldsymbol{\Psi}^{\star 11} & \cdots & \boldsymbol{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Psi}^{\star R1} & \cdots & \boldsymbol{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \boldsymbol{c}_t^{\star 1} \\ \vdots \\ \boldsymbol{c}_t^{\star R} \end{bmatrix}$ $t = 1, \dots, T$	(5.27)
$\beta_{ijt} = \{0{,}1\}, \mu_{ijt} = \{0{,}1\}, \quad \forall\, (i,j) \in L', t = 1, \dots, T$	(5.28)
$S_{it}^{k'} > 0, \quad \forall i \in N_+, \forall j \in N_-, k' = 1, \dots, K', t = 1, \dots, T$	(5.29)
$c_{rt}^{\star k} > 0, q_{rt}^k > 0, Q_{rt}^k > 0, \omega_{kt}^r = \{0{,}1\},$ $r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T$	(5.30)

The proposed formulation optimizes the restoration efforts associated with a transportation network in the aftermath of a disruptive event. Recall that the network is presented by an undirected graph $G = (N, L)$, with set of nodes N and set of links L. Nodes and links affected by a disruption are represented with sets N' and L', respectively. The objective function explores a restoration schedule of disrupted links that leads to the maximum proportional reduction in economic losses across the time horizon. Eq. (5.19) restricts the total flow of all commodities on each link (i, j) to at most its pre-disruption capacity u_{ij}. After a disruption, the capacity of each disrupted link $(i, j) \in L'$ is reduced to zero unless it is completely recovered and becomes operational again, as shown in Eq. (5.20). Eq. (5.21) represent the flow balance constraint for all commodities in and out of supply, demand, and transshipment nodes. In the aftermath of disruption we maintain the flow balance in each node by defining ,as the slack variable $S_{it}^{k'}$ which captures: (i) the remaining supply of each industry across each supplier, (i.e., $S_{it}^{k'}$ $\forall i \in N_{+}^{k'}$), (ii) the unmet demand of each industry across each demand node , (i.e., $S_{it}^{k'}$ $\forall i \in N_{-}^{k'}$). Note that $b_{i}^{k'}$ is a positive value for supply nodes, $\forall i \in N_{+}^{k'}$, a negative value for demand nodes, $\forall i \in N_{-}^{k'}$, and it is zero for transshipment nodes, $\forall i \in N_{=}$. Eqs. (5.22) and (5.23) schedule disrupted links for restoration. Eq. (5.22) shows that each disrupted link is recovered in one time period, and when it is recovered, it should remain operational for the remainder of the time horizon, Eq. (5.23). Eq. (5.24) calculates the consumption perturbation of each industry k, remaining in each supplier node, $S_{it}^{k'}$ $\forall i \in N_{+}^{k'}$, or each unsatisfied demand node, $S_{it}^{k'}$ $\forall i \in N_{-}^{k'}$, in each region r at each time t with respect the total production of industry k in each region r, $\hat{x}_k^r$. In Eq. (5.25), ω_{kt}^r activates the impact of inoperability of commodities in industry k in region r at time t in Eq. (5.24) only if there exists any unsatisfied demand of commodities in industry k in that region. Eqs. (5.26) and (5.27) calculate the inoperability level and total economic loss of each industry, k, in each region, r ,at time, t, respectively. In Eq. (5.26), q_t^r is the inoperability matrix, $k \times 1,\ \forall k \in K$, of all industries in each region r which capture the consequences of the existence of unsatisfied demand of each industry k on the output of that industry which is required to be minimized as the result of optimal schedule of disrupted links, Eq. (5.27).

5.3 Illustrative Example: Multi-Modal Freight Transport in Oklahoma and Surrounding Region

We demonstrate the proposed model on a case study based on a multi-modal freight transportation network, consisting of three interstate highways, railways, and inland waterway that connect Mississippi River Navigation System through two ports. This infrastructure plays a significant role in transporting commodities produced in the state of Oklahoma and sent to consumers in neighboring states, and so contrariwise. We employ the case study to implement the proposed model and evaluate and analyze the restorative efforts from different perspectives, such as, economy loss of each type of produced commodity in each region and network resilience behavior within restoration horizon. Three disruption scenarios are defined as the complete disruption of four different transshipment nodes. Four combined demand/supply nodes are considered in surrounding states are connected to three main supply/demand nodes within Oklahoma multi-modal freight transportation network. the multi-regional, multi-industry economy loss in the aftermath of each disruptive scenario determines the optimal schedule of disrupted links to be restored with results in maximum economy saving during restoration process.

5.3.1 Supply-Demand Network

Figure 5.3 shows the multi-modal freight transportation network, which sends and receives flows of different commodities from the industry sectors within the state of Oklahoma to the neighboring states and from surrounding states to the state of Oklahoma, respectively. The network consists of a part of interstate highways I-35, which connects Oklahoma to the north-south corridor, and I-40 and I-44, which is connected through the east-west corridor. Part of US highways 169 and 165 within Oklahoma connects the Port of Catoosa and the Port of Muskogee to the interstate highway network. Two intermodal rail-truck facility, one in Oklahoma City near the junction of I-35 and I-40, and the other one in Tulsa Oklahoma, which belongs to Burlington Northern Santa Fe (BNSF) railroad, are considered in the infrastructure of the network. We also include a part of the US inland waterway which connects the connects the Port of Catoosa and the Port of Muskogee to the Port of New Orleans, LA (node 5), the Port of Chicago, IL (node 7), the Port of Little Rock, AR (node 6), and the Port of Texas City, TX (node 4).

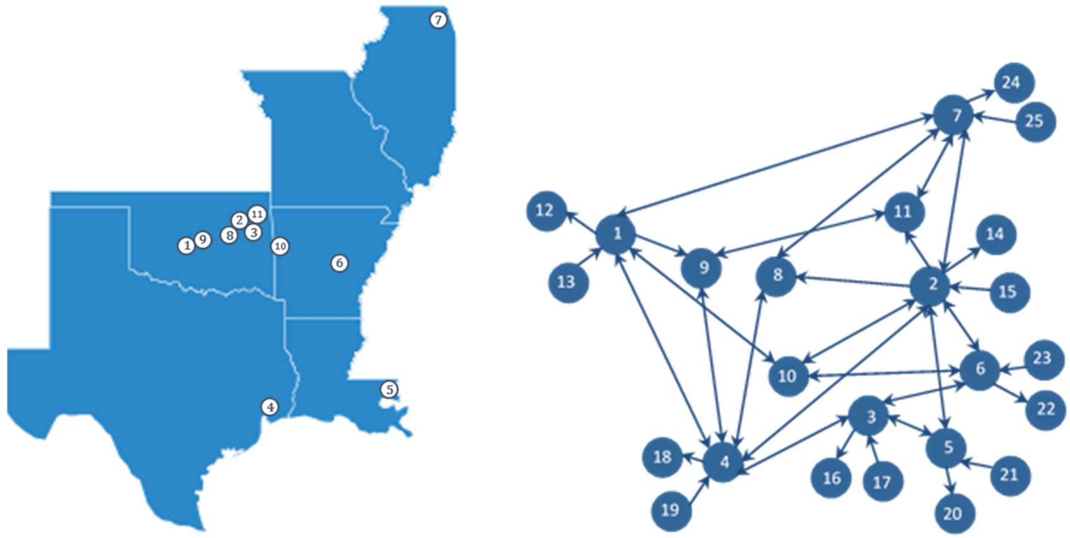


Figure 5.3. Representations of (a) spatial location of multi-modal nodes in Oklahoma and surrounding states, and (b) the connected transportation network.

Based on NAICS, 62 industries operate in each of the five states, therefore $\mathbf{A}^{\star}$ matrix regionalized for each state is 62×62. Although the focus of this work is to study the interaction of remained supply/unsatisfied demand and economy loss in the five regions, we also are interested in tracking the impacts of disruptions of these five states on other states which are not involved in disruption, yet are affected by its consequent negative impacts associated with their economy loss. Therefore $\mathbf{A}^{\star}$ matrix is 620×620 involved in network disruption and five affected regions by marginal disruption effects. We consider six primary industries export and import commodities through each five states. Discussed previously, it is assumed that two types of commodities belong to each industry as defined by NAICS economic sectors, and each node within the network is considered to be home to both suppliers or consumers of multiple commodities or transship the flow without adding or reducing any amount of flow. Based on the combined estimated annual supply and demand in tons for the associated industries and states compiled from different databases (US Army Corps of Engineers 2013, Tulsa Port of Catoosa 2013, Bureau of Transportation Statistics 2010a,b, Port of Muskogee 2013, Bureau of Economic Analysis 2010), a list of monthly supply and demand is presented in Table 5.2 (assuming constant monthly demand, or annual demand divided by 12).

Table 5.1. Economic losses, in million USD, within the state of Oklahoma after planning for adaptive capacity.

		Industry					
		311	**324**	**325**	**327**	**333**	**339**
Supply	Oklahoma City (1)	362526	0	300501	183188	23790	118242
	Port of Catoosa (2)	50244	454911	284685	25268	2470	424
	Port of Muskogee (3)	0	33962	0	31886	0	30021
	Texas (4)	23250	0	21750	0	0	577
	Louisiana (5)	993	3828	36528	0	7174	0
	Arkansas (6)	0	0	60000	635	17000	1100
	Illinois (7)	356	0	448	0	70000	0
Demand	Oklahoma City (1)	23250	0	60000	0	17000	1100
	Port of Catoosa (2)	1064	3828	36976	635	7174	577
	Port of Muskogee (3)	285	0	21750	0	70000	0
	Texas (4)	97281	316905	204006	0	25838	30154
	Louisiana (5)	50244	18449	0	0	267	0
	Arkansas (6)	265245	153518	381180	41038	156	54494
	Illinois (7)	0	0	0	199304	0	64039

5.3.2 Freight Movement and Disruption

To parametrize the MCNF model, the cost vector is computed based on the transportation mode and the mileage of the distances between nodes: the per ton-mile for a barge is estimated at \$0.97, compared to \$2.53 for rail, and \$5.35 for trucking (Arkansas Waterway Commissions 2014). Assuming that the total supply of commodity k is equal to the total demand of the same commodity throughout the network, as shown in Table 5.2, a baseline flow resulted in no remaining commodities at supply nodes and no unsatisfied demand at demand nodes when there is no disruption to the functionality of the network.

In the illustrative example, disruption scenarios are defined as the removal of three network components, (i.e., nodes), at a time. It is assumed that a disruption, or the removal of a particular network component, lasts for a period of one month. Assuming that annual industry production accumulates consistently across the year (i.e., neither production nor interdependency relationships vary day-to-day, week-to-week, month-to-month), a smaller month-long time horizon is considered here as an appropriate proportion of a year to calculate the particular disruptive event cascading effect (e.g., a two-week closure of port facilities (Pant et al. 2011)). Focusing on the economy each of four states, and considering supply nodes within each state interacting with demand nodes in surrounding states, undelivered commodities remaining with suppliers or unsatisfied demand at demand nodes, as represented by $S_{it}^{k'}$, affect industry output and result in propagated inoperability through many of the interconnected industries. In the illustrative example, shown in Table 5.3 and Table 5.4, three disruption scenarios are defined as the removal of a combination of four nodes among eleven transmission nodes in a random order. In the first scenario nodes 10, 9, 11 and the transmission node associated with node 7 are disrupted. The second scenario considers nodes 8, 9, 11 and the transmission node associated with node 4. The third scenario disables nodes 10, 8, 11 and the transmission node related to node 1. We assume that a disrupted node disconnects all its related links completely.

In the illustrative example, three supply/demand nodes are within the state of Oklahoma and the four supply/demand nodes are located in Texas, Louisiana, Arkansas, and Illinois. Table 5.3 and Table 5.4 report $\sum_{k' \in N_{+}^{k'}} \sum_{i \in (N_{+}^{r} \cap N_{k})} S_{it}^{k'}$, or the sum of the slack (remaining supply) by commodity at the supply nodes when different network components are disrupted, and $\sum_{k' \in N_{-}^{k'}} \sum_{i \in (N_{-}^{r} \cap N_{k})} S_{it}^{k'}$, the sum of the slack (unsatisfied demand) by commodities at the demand nodes when different network components are disrupted, respectively, omitting the flow on the disrupted component from the baseline flow within the network. As shown in Table 5.3, the *Petroleum and coal* industry (324) is directly vulnerable in all disruption scenarios except for the loss of link (1,7), while the *Food and beverage and tobacco* industry (311) would be affected only by the loss of link (2,5).

Table 5.2. Tons of remaining commodities at suppliers with the removal of network components.

Disruption Scenario	Region	Sum of remaining commodities at supply nodes (tons)					
		311	324	325	327	333	339
Scenario 1	Oklahoma	412770	488873	585187	240342	26262	148687
	Texas	23250	0	21750	0	0	577
	Louisiana	993	3828	36528	0	7174	0
	Arkansas	0	0	60000	635	17000	1100
	Illinois	0	0	0	0	0	0
Scenario 2	Oklahoma	362526	448612	382487	240342	26262	138687
	Texas	23250	0	21750	0	0	577
	Louisiana	993	3828	36528	0	7174	0
	Arkansas	0	0	60000	635	17000	1100
	Illinois	356	0	448	0	70000	0
Scenario 3	Oklahoma	412770	454911	585187	208456	26262	118666
	Texas	23250	0	21750	0	0	577
	Louisiana	0	0	0	0	0	0
	Arkansas	0	0	0	0	0	0
	Illinois	0	0	0	0	0	0

Table 5.3. Tons of unmet demands at demand nodes with the removal of network components.

Disruption Scenario	Region	Sum of unsatisfied commodities at demand nodes (tons)					
		311	324	325	327	333	339
Scenario 1	Oklahoma	24599	3828	118726	635	94174	1677
	Texas	97281	316906	204006	0	25838	30154
	Louisiana	50244	18450	0	0	267	0
	Arkansas	265245	153518	381180	41038	156	54494
	Illinois	0	0	0	199304	0	0
Scenario 2	Oklahoma	24599	3828	118726	635	94174	1677
	Texas	97281	316906	204006	0	25838	30154
	Louisiana	50244	18450	0	0	267	0
	Arkansas	265245	153518	381180	41038	156	54494
	Illinois	0	0	0	199304	0	64039
Scenario 3	Oklahoma	24599	3828	118726	635	24174	1677
	Texas	97281	316906	204006	0	25838	30154
	Louisiana	50244	18450	0	0	267	0
	Arkansas	265245	119556	381180	9152	0	24473
	Illinois	0	0	0	199304	0	0

5.4 Results and Analysis

As each of four states includes supply and demand nodes, failure in the form of the inability of suppliers to export commodities/demands to receive commodities is modeled as a inoperability perturbation. Other industries within each of the four states as well as other states, which is not involved in disrupted network directly, will be affected by interdependent effect of this failure, as captured by q_{rt}^{k} in matrix q_{t}^{R} for each region in Eq. (5.7), representing the extent to which an industry output will not be products, or an industry input will not be received. The effect of the disruption on the economy loss of each state is captured by Q_{t}^{r}.

Given the remaining commodities left at supply nodes and unsatisfied demands in demand nodes, shown in Table 5.3 and Table 5.4 respectively, inoperability perturbation is calculated with Eqs. (5.26) and (5.27) and depicted in Table 5.5. The *Machinery* industry (333) is the most vulnerable in the presence of each three disruptive scenarios. Each these disruptive scenarios also affects the operability of the *Miscellaneous manufacturing* industry (339), yet in lesser extent than industry (333). The operability level in Arkansas is dependent on the connectivity of transshipment nodes 9 and 11 to the rest of the network.

Table 5.4 represents a detailed report of the maximum economic loss in the aftermath of each disruption scenarios. Each column is associated with one disruption scenario and includes: (i) the total economic loss resulted from each disruption scenario, (ii) the maximum economic loss related to each state and each industry, (iii) the last column presents a detailed report of the maximum economic loss related to each industry in each state. Recovery decisions in terms of the order in which disrupted components should be recovered are made based on the impacts on the total economy, as shown in Figure 5.4. And, Figures 5.5-5.10 present regional and industry-based impacts of the recovery decisions.

Table 5.4. Economic losses, in million USD, within the state of Oklahoma after planning for adaptive capacity.

Formulation	Region	Industry	Q_{max} Scenario1	Scenario2	Scenario3
Total economic loss $\sum_{r=1}^{R}\sum_{k=1}^{K} Q_{rt_d}^{k}$			14707.40	12711.9	13340.7
The economic loss for each region $\sum_{k=1}^{K} Q_{rt_d}^{k}$	Oklahoma		558.49	494.58	631.12
	Texas		1218.60	1199.37	530.33
	Louisiana		262.51	236.42	244.68
	Arkansas		6917.85	5832.27	129.17
	Illinois		5749.97	4949.30	6065.67
The economic loss for each industry $\sum_{r=1}^{R} Q_{rt_d}^{k}$		311	716.28	633.01	1737.92
		324	606.02	519.83	419.01
		325	276.26	242.88	1105.74
		327	148.63	132.16	178.27
		333	6659.87	5761.98	6532.99
		339	1866.38	1586.53	5104.71
Inoperability	Oklahoma	311	0.00546	0.00494	0.00322
		324	0.04501	0.04487	0.00090
		325	0.00210	0.00187	0.00145
		327	0.01148	0.01051	0.00592
		333	0.00252	0.00336	0.00000
		339	0.01135	0.00967	0.01016
	Texas	311	0.00436	0.00467	0.00399
		324	0.00022	0.00049	0.00020
		325	0.00151	0.00158	0.00138
		327	0.00234	0.00391	0.00214
		333	0.04866	0.04738	0.04407
		339	0.00556	0.00540	0.00506
	Louisiana	311	0.00188	0.00182	0.00048
		324	0.00019	0.00018	0.00005
		325	0.00283	0.00248	0.00241
		327	0.00326	0.00322	0.00054
		333	0.00000	0.00000	0.00000
		339	0.00302	0.00260	0.00258
	Arkansas	311	0.06400	0.05389	0.06038
		324	0.04101	0.03450	0.03883

	325	0.01482	0.01253	0.01396
	327	0.04483	0.03777	0.04226
	333	0.42954	0.36238	0.40553
	339	0.10744	0.09039	0.10184
Illinois	311	0.00441	0.00382	0.00404
	324	0.00030	0.00027	0.00028
	325	0.00149	0.00129	0.00133
	327	0.00288	0.00254	0.00257
	333	0.07121	0.06123	0.06244
	339	0.00521	0.00444	0.00475

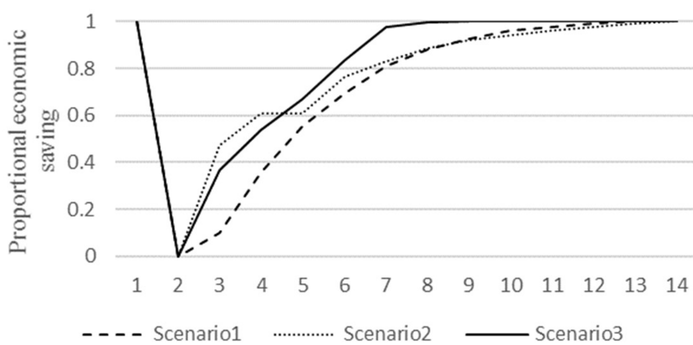
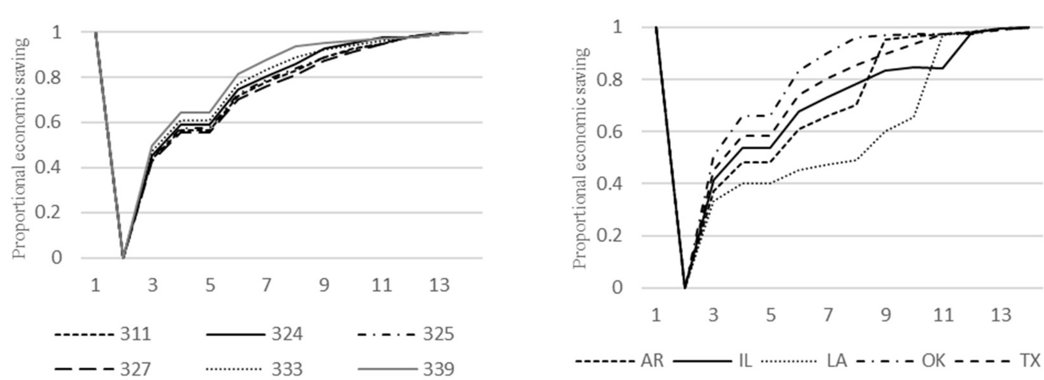
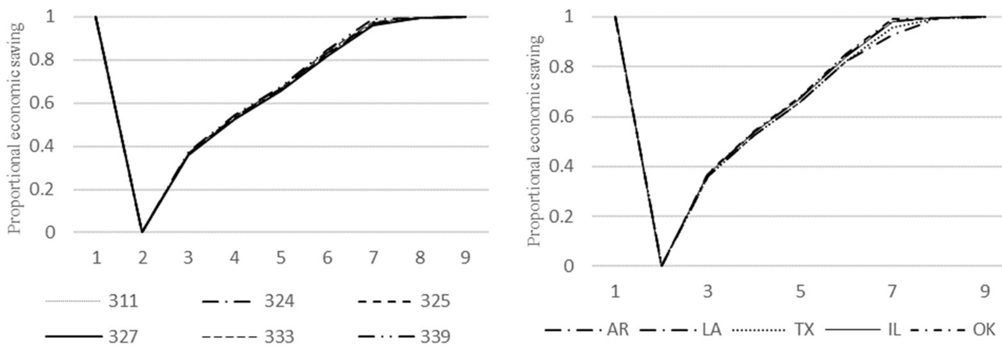


Figure 5.4. Total proportional economic saving for each disruption



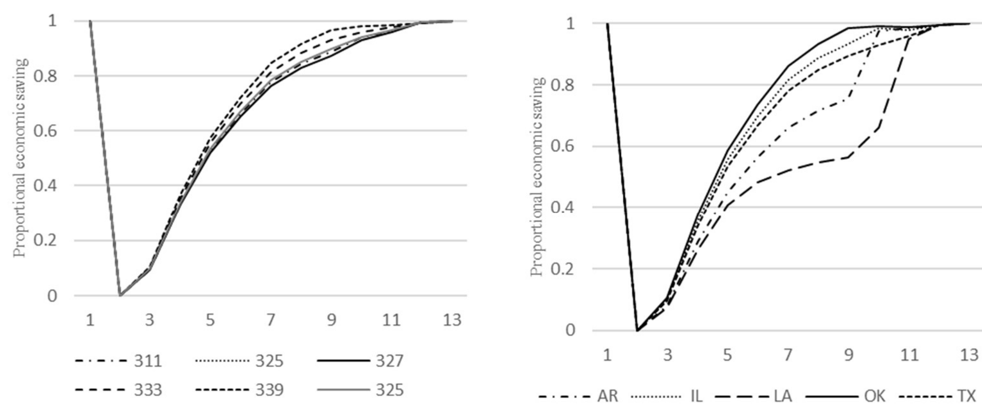
(a) (b)

Figure 5.5. (a) Proportional economic saving for each industry, (b) Proportional economic saving in each region (Scenario 1)



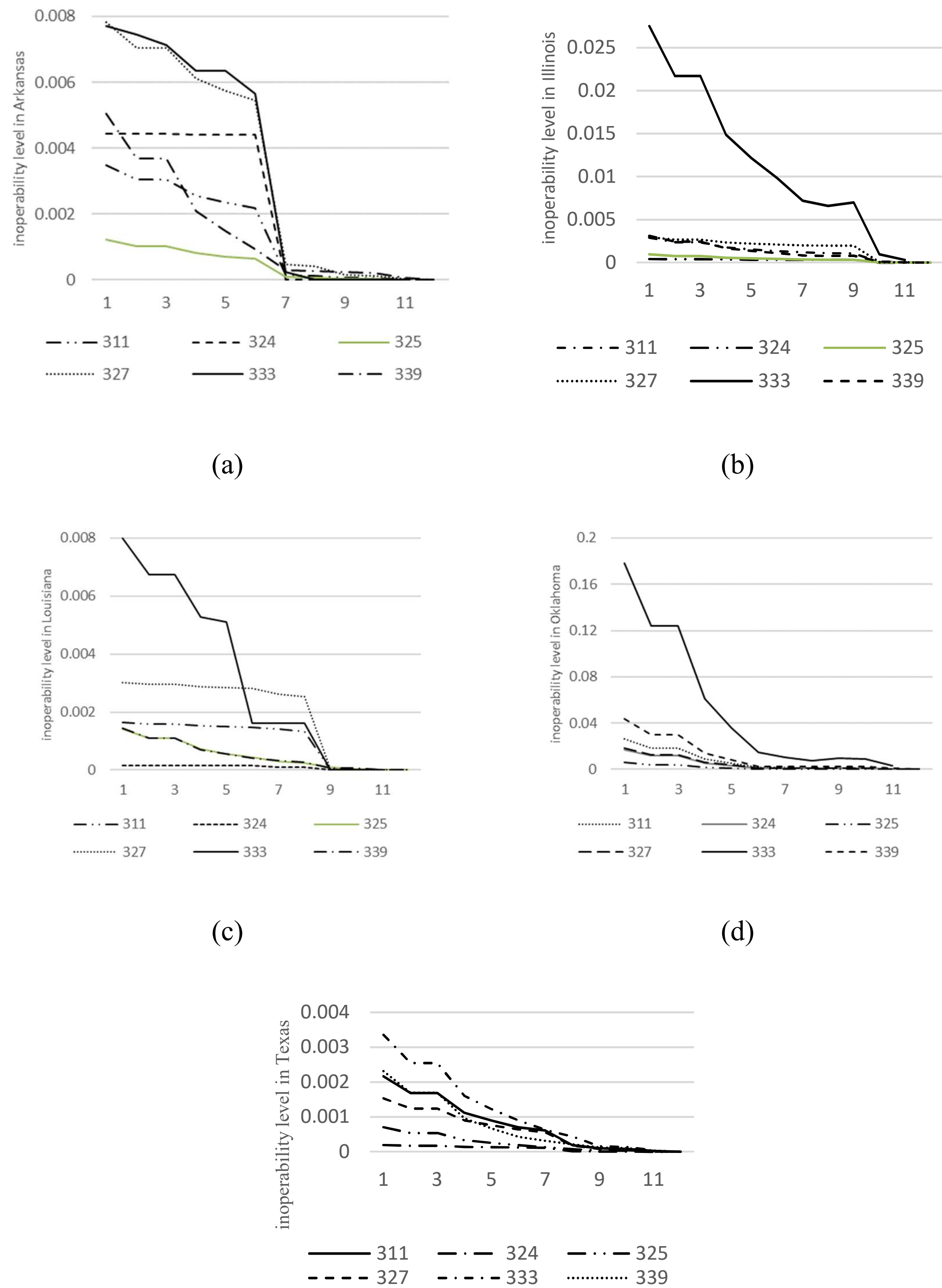
(a) (b)

Figure 5.6. (a) Proportional economic saving for each industry, (b) Proportional economic saving in each region (Scenario 2)



(a) (b)

Figure 5.7. (a) Proportional economic saving for each industry, (b) Proportional economic saving in each region (Scenario 3)



(a) (b)

(c) (d)

(e)

Figure 5.8. The inoperability level of each industry in: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, (e) Texas (Scenario 1)

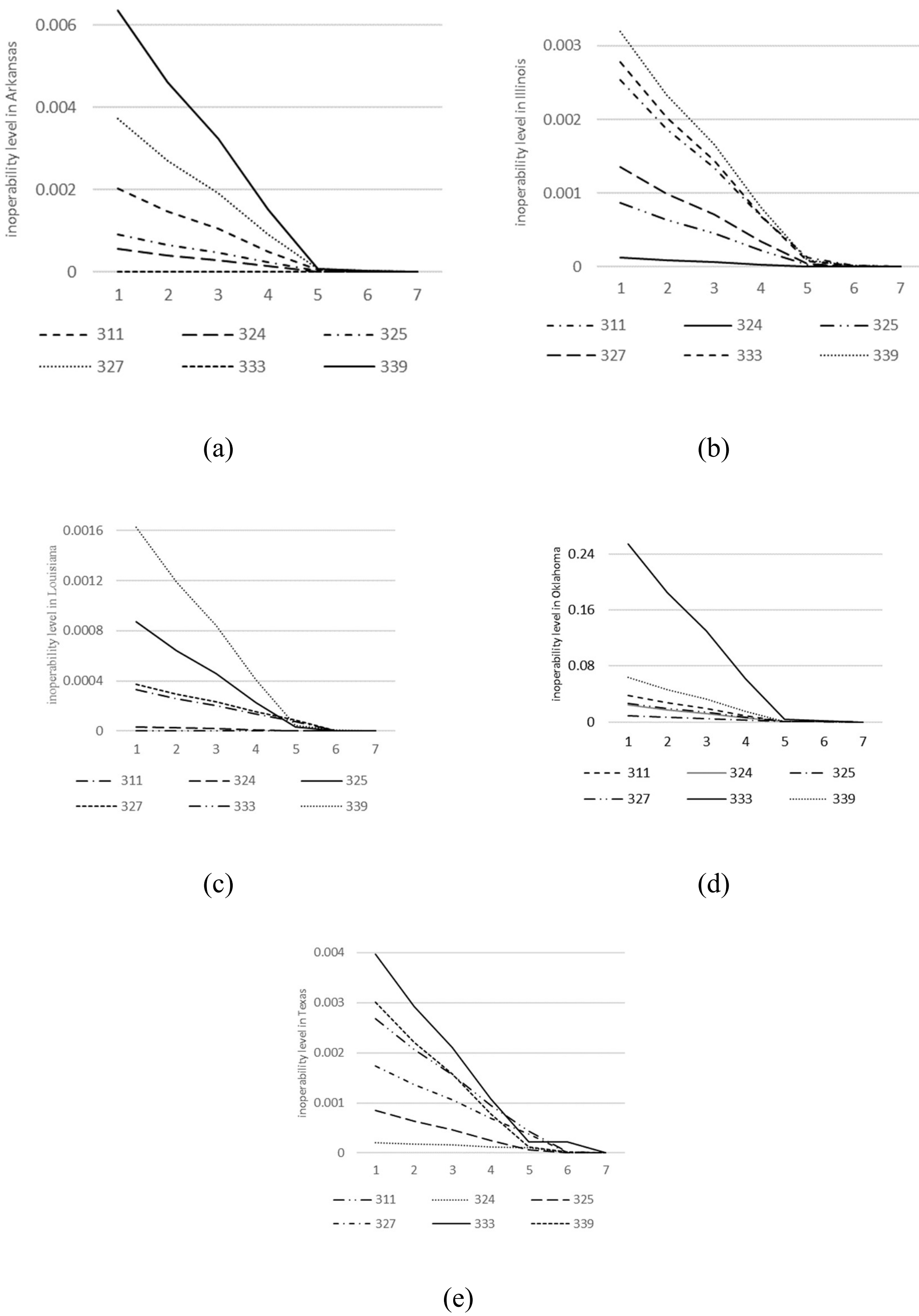
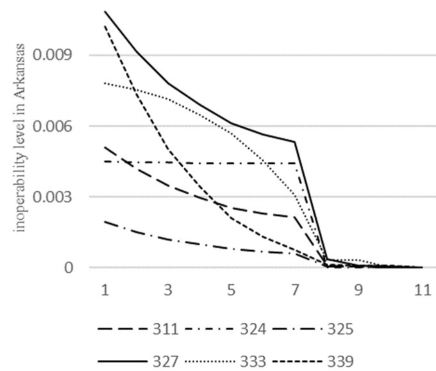
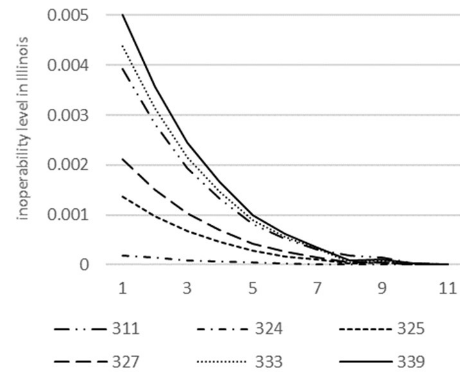


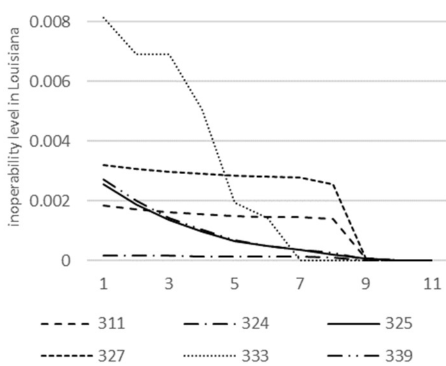
Figure 5.9. **The inoperability level of each industry in: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, (e) Texas (Scenario 2)**



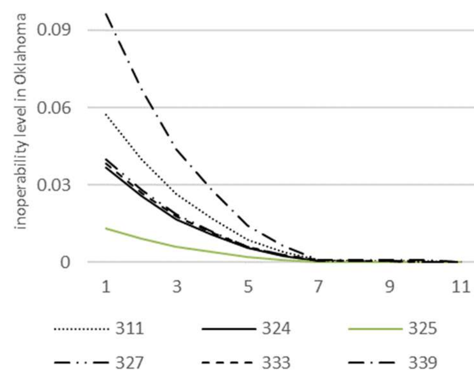
(a)



(b)



(c)



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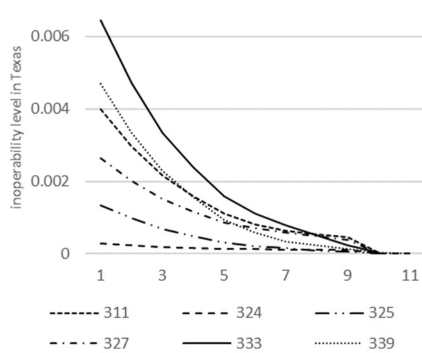

(e)

Figure 5.10. The inoperability level of each industry in: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, (e) Texas (scenario 3)

CHAPTER 6

CONCLUDING REMARKS

6.1 Summary and Conclusions

The overriding theme of this dissertation is to study the freight transportation resilience considering economic impacts. Resilience has been defined based on the three aspects of the resilience capacity proposed by Vugrin and Camphouse (2011): (i) absorptive capacity, or to the extent a network is able absorb shocks from disruptive event, (ii) adaptive capacity, or the extent to which a system can quickly adapt after a disruption by temporary means, and (iii) restorative capacity, or the extent to which the system can recover from a disruption or be reconstructed in the long-term. Also, It is sought to measure the network vulnerability by considering the multi-regional, multi-industry impacts of a disruption within a freight transportation network.

In the first step, an integrated framework is developed to measure the economic impacts of a disruption within a multi-modal freight transportation network using a typical multi-commodity network flow formulation and an economic interdependency model. And, a measure of transportation network vulnerability is proposed to analyze a broader perspective on freight transportation network vulnerability with a means to measure importance of network components considering economic impacts of degradation of transportation network. The primary contribution of this approach is the integration of the multi-commodity network flow representation of the multi-modal transportation network with the interdependent, multi-industry economic model and a framework to measure a transportation network component importance considering its multi-industry impact. A stylized case study of a multi-modal transportation network in the state of Oklahoma is considered to illustrate the developed vulnerability analysis paradigm.

In the second step, focusing on the first component of resilient capacity of a system, it is sought to lessen the effects of disruptions by investing in hardening both the infrastructure (e.g., backup equipment) and industry sectors. The interdependent nature of industries has been considered in resource allocation. And, a modeling and analysis framework to allocate limited resources to harden industry sectors to enhance the absorptive capacity of the total economy is developed. The interdependent adverse effects of a disruption are measured using a risk-based interdependency model and an exponential resource allocation model is introduced to formulate the risk reduction. Finally, proposing an integrated optimization model, it is sought how a limited budget could be allocated to multiple industries to enhance the whole interdependent system's economic resilience. A risked-based economic interdependency model is used to measure the propagation of a failure through industries. Sources of uncertainty in this data-driven model are considered, and a soft-robust optimization model is proposed to devise budget allocation under uncertainty. The approach is illustrated with an inland waterway port case study.

In the third step, adaptive capacity is emphasized and contingent rerouting strategies are discussed to manage the supply-demand network after a disruptive event to lessen the total economic impact. An optimization formulation is proposed to accommodate the flow through the residual network and maintain the productivity of the economy of the desired region by (i) integrating a multi-commodity network flow model, representing a multi-modal freight transportation network, with a risk-based economic interdependency model, to capture the propagation of the failure in a group of interconnected industries, and (ii) defining a measure of adaptive capacity to valuate rerouting strategies. Results suggest a successful avoidance of maximum potential loss in high dollar industries such as *Petroleum and coal products* (324) and *Miscellaneous manufacturing* (339), and a consequent static resilience in the economy of the state, as the average maximum loss could be avoided by more than 50%.

Finally, network resilience enhancement considering economic impacts via restorative capacity is discussed. Freight Infrastructure as a means to promote economic productivity is considered, and an infrastructure network recovery optimization via demand satisfaction or network connectivity accounting for multi-industry economic impacts is proposed. The focus is on measuring the effectiveness of restorative capacity on economic productivity with the proportional value of the maximum loss that can be avoided by recovery decisions. And, regional and industry-based economic impacts of recovery decisions are analyzed. It is shown that multi-regional, multi industry perspective changes the resilience decisions considering total economic productivity though it might not be of benefit to all the regions/industries.

6.2 Future Directions

The methods developed in this dissertation can be employed and expanded in several directions. Some of them are discussed below.

The vulnerability analysis perspective proposed in this study can be implemented to highlight priorities in maintaining certain network components (to reduce common-cause failure), or in rerouting of commodity flows after a disruption. There also exists an opportunity to extend the base approach discussed in this work to analyze network completion strategies where capacity enhancement (e.g., link capacity) and additional transportation facilities (e.g., added links/nodes) could harden the network around the most vulnerable components. Further, longer term transportation infrastructure design plans could be informed by this kind of analysis. Also, the proposed model for absorptive capacity can be implemented in a network of freight infrastructure.

This initial formulation proposed to plan for adaptive capacity can be further improved by accounting for the real-world intermodal container planning considerations and other dynamic issues. Complementary models to plan for system resilience as a function of absorptive and restorative capacity, as well as the adaptive capacity-focused formulation proposed here, could more effectively highlight the tradeoffs among different resilience capacity planning perspectives.

In the proposed network recovery model, it is assumed that recovery time is equal for all disrupted components and it is just possible to recover one link at a time period. The model can be improved by considering proportional recovery and scheduling crews to recover multiple disrupted components at a time period.

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