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A multi-industry economic impact perspective on adaptive capacity planning in a freight transportation network

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ABSTRACT

The multi-modal freight transportation network plays a vital role in maintaining commodity flows across multiple industries and multiple regions. As such, the effects of large-scale disruptive events could result in the closure of key transportation nodes and links, causing disruptions in commodity flows and larger disruptions to industries requiring those commodities for economic productivity. This work integrates a multi-commodity network flow formulation with an economic interdependency model to quantify the multi-industry impacts of a disrupted transportation network to devise contingent rerouting plans to strengthen the network's adaptive capacity. The formulation proposed here is illustrated with a freight transportation planning case study in the state of Oklahoma, considering disruptive scenarios in which a network component is lost and how the proposed approach improves total economic productivity following a disruption.

1. Introduction and motivation

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" [White House 2013]. 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 [US Department of Transportation, 2013].

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 [US Department of Transportation, 2015]. Over the next 30 years, transportation's contribution to the US gross domestic product is expected to grow to approximately $1.6 trillion [US Department of Transportation, 2015]. 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 [The House Committee on Transportation and Infrastructure 2013; US Department of Transportation, 2014; Yusta et al., 2011]. Emphasis has been placed on "securing and managing flows of people and goods" along transportation networks [DHS, 2014].

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 [Kengpol et al., 2012; Miller-Hooks et al., 2012; Lee and Kim 2010]. Transportation network disruptions lead not only to physical damage, but also to an interruption of economic productivity across multiple industries due to infrastructure inoperability [Tierney 1997; Webb et al., 2000, Ham et al., 2005; Pant et al., 2011; Park et al., 2011]. As such, a comprehensive discussion of transportation network resilience should account for multi-industry impacts.

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

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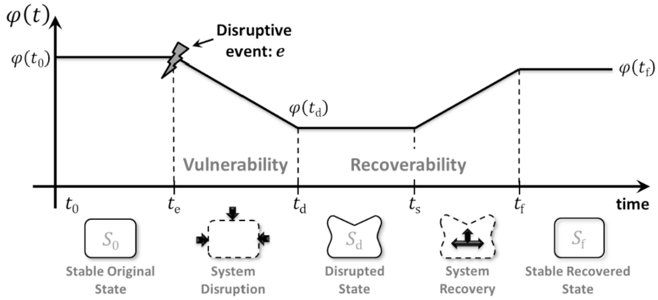


Fig. 1. System performance, $\varphi(t)$, trajectory facing a disruptive event [Henry and Ramirez-Marquez 2012].

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);Patterson et al., (2006); Zobel (2011); Sarre et al., (2014)). In particular, the paradigm proposed by Henry and Ramirez-Marquez (2012), along with several applications and extensions [Barker et al., 2013; Pant et al., 2014a; Baroud et al., 2014], quantifies system resilience as a function of time. Fig. 1 depicts system performance, generally quantified with function $\varphi(t)$, before, during, and after a disruptive event (e.g., $\varphi(t)$ could describe traffic or commodity flow in a transportation network over time). Fig. 1 highlights two dimensions of resilience: *vulnerability*, or the extent to which performance degrades after a disruption [Zio et al., 2008, Jonsson et al., 2008, Zhang et al., 2011], and *recoverability*, or the ability to return to a stable, desired level of performance [Barker et al., 2013; Pant et al., 2014a].

Similarly, Vugrin and Camphouse (2011) suggest that the *resilience capacity* of a system is a function of three components: (i) *absorptive capacity*, or the ability of a system to absorb or withstand a disruption with essentially no change in performance, (ii) *adaptive capacity*, or a short-term means to quickly regain a desired performance, and (iii) *restorative capacity*, or the long-term repair of physical damage. Vugrin and Camphouse (2011) pose absorptive, adaptive, and restorative capacities as first, second, and third "lines of defense," where the next is engaged if the previous fails. In a transportation network context, (i) absorptive capacity may describe the physical characteristics of, say, a bridge to withstand the shock of an earthquake, (ii) adaptive capacity may include alternate paths in the network that could be engaged quickly to work around damaged areas, and (iii) restorative capacity may describe the long-term bridge reconstruction activities required to restore the transportation network. Relative to Fig. 1, the collection of absorptive and adaptive capacities may reduce vulnerability, while restorative capacity would improve recoverability.

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 Fig. 2, 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., 2014a, b], 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. (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.

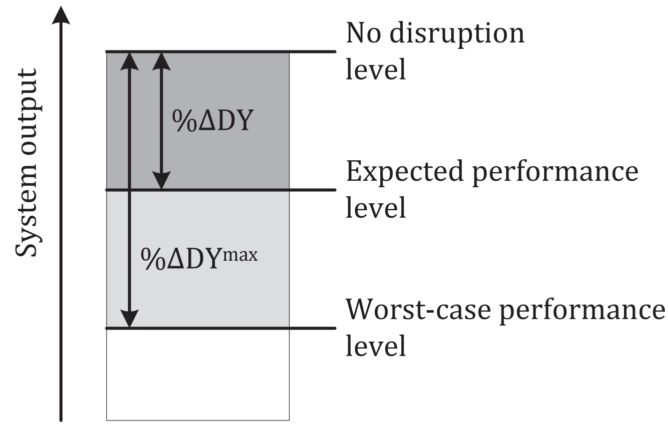


Fig. 2. The performance components of static resilience [Rose 2009; Pant et al., 2014b].

$$\text{static resilience} = \frac{\%\Delta DY^{max} - \%\Delta DY}{\%\Delta DY^{max}} \tag{1}$$

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. In particular, we integrate adopt an input-output model to represent multi-industry impact, chosen because of its ease in integration with an optimization formulation (discussed in detail later). Another popular option for multi-industry impact is the computable general equilibrium (CGE) model, a multi-layer agent-based simulation meta model that simulates agents in an economy that react to price and quantity signals, and such a model does not lend itself so easily for use in a multi-commodity network flow optimization model.

This paper is arranged as follows. Section 2 describes the proposed approach to plan for adaptive capacity in a disrupted freight transportation network, developing a model to accommodate flow through the residual network after disruption by integrating a multi-commodity network flow formulation with a risk-based economic interdependency model. Section 3 presents an illustrative example, developed based on a partial freight transportation network within the State of Oklahoma consisting of three important business economic areas and the multi-modal freight network infrastructure which facilitates trade with centers out of the state. Section 4 provides concluding remarks and future research avenues of this work.

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

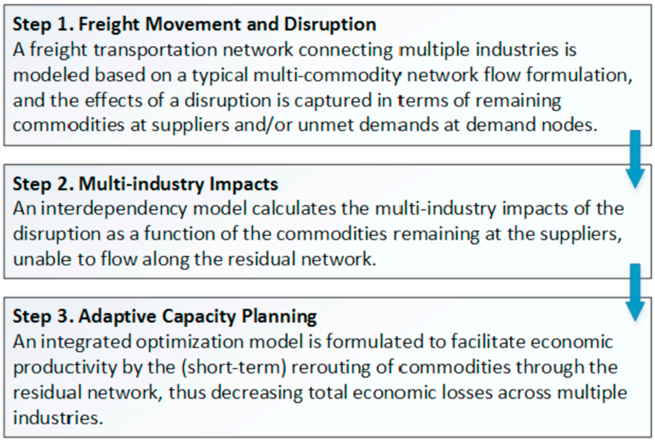


Fig. 3. Three-step approach to planning for adaptive capacity with multi-industry impacts.

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 Fig. 3.

2.1. 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);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]). In this work, when a disruption interrupts the movement of commodities through the network, a tactical contingent rerouting plan is sought, for the period of disruption, to maintain the functionality of the supply-demand network as much as possible.

The topology of the multi-modal freight transportation network, as well as corresponding supply and demand nodes, must be extracted to model and analyze the behavior of the network before and after disruption. The transportation network is considered to be a facilitator of K interacting industries, where multiple supply and demand nodes of commodity k could represent a particular industry. Based on a conventional MCNF model, the network is defined on directed graph $G = (N, L)$, where N is a set of nodes, each of which could be home to either suppliers or consumers of multiple commodities, and L is a set of links connecting nodes. For this graph, K denotes the number of commodities in a network instance, each representing an industry. Let f_{ij}^k denote the decision variable associated with the flow quantity of commodity $k \in \{1,\dots,K\}$ on link $(i, j) \in L$. Let parameter w_{ij}^k denote the associated per-unit transportation cost. The costs differ based on link properties such as length and transportation mode (e.g., waterway, railway, highway). Let parameter u_{ij} denote the total flow capacity of link $(i, j) \in L$. That is, the capacity of each link is a shared or "bundle" constraint for all commodities flowing on the link. The supply/demand requirement of commodity k at node $i \in N$ is denoted by parameter b_i^k. If b_i^k is positive, then node i is a supply node of commodity k. Similarly, if b_i^k is negative, then node i is a demand node for commodity k. If b_i^k is zero, the node i is a transshipment node with respect to commodity k. The mathematical formulation for the MCNF problem is provided in Eq. (2). Without loss of generality, each node within the network can be home to either suppliers or consumers of multiple commodities. The set of nodes then can be partitioned into three mutually exclusive sets: $N = (N_-, N_+, N_0)$ where N_- denotes the set of nodes representing nodes which are home to consumers, N_+ denotes which are home to suppliers, and N_0 denotes all transshipment nodes. Each commodity belongs to an industry in the economy as defined by the North American Industry Classification System (NAICS).

$$
\begin{aligned}
\min\ & \textstyle\sum_{(i,j)\in L} \sum_k w_{ij}^k f_{ij}^k \\
\text{s.t.}\ & \textstyle\sum_k f_{ij}^k \le u_{ij}, \quad \forall\ (i, j) \in L \\
& \textstyle\sum_{(i,j)\in L} f_{ij}^k - \sum_{(j,i)\in L} f_{ji}^k = b_i^k, \quad \forall\ (i, j) \in L,\ k = 1,\dots,K \\
& f_{ij}^k \ge 0, \quad \forall\ (i, j) \in L,\ k = 1,\dots,K
\end{aligned} \tag{2}
$$

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. 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. 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.

A disruption scenario is defined as the set of network components that are impacted, the degree to which they are disabled, and the operating conditions (e.g., network activity, link/node capacities) of the network prior to the disruption regardless of the initiating event that causes the disruption. Different approaches to model a transportation network disruption have been offered (e.g., losing a bridge, a road segment, or a hub [Jenelius and Mattson, 2012; Burgholzer et al., 2013; Rupi et al., 2014]), with most approaches considering one component being affected [Faturechi and Miller-Hooks 2015]. A disrupted network component may be rendered completely inoperable by a disruption (e.g., losing a road completely due to a bridge collapse), or its functionality may drop to a lower level (e.g., an accident blocking a single lane of an interstate highway segment). Simulating the disruption scenario enables the evaluation of the impact of the failure. Impacts can be considered as the direct associated failures in network operability (e.g., flow or capacity reduction) or consequential failures (e.g., the economic impacts affecting the production and consumption of flows) [Matisziw and Murray 2009]. It takes time to recover affected network components (e.g., after Hurricane Katrina, it took up to six months in southern regions to recover highway networks, whereas northeast regions recovered much more quickly [DesRoches, 2006]; after an I-40 bridge collapsed in Oklahoma following a barge collision in 2002, traffic was rerouted for nearly two months while crews rebuilt the infrastructure [Aydin and Shen, 2012]). As such, devising an efficient and effective contingent rerouting strategy immediately after extreme events would assist the economic productivity of the disrupted region.

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, as calculated in Eq. (1). 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.

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. 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].

Under a static equilibrium, the total output of industry (or economic sector) k is distributed to other industries and also satisfies external (consumption) demand. Under a proportionality assumption, this equilibrium condition is described with $x_k = \sum_{r=1}^{K} z_{kr} + c_k$, where x_k is the total output of industry k, z_{kr} is the input of industry k to the production of industry r (intermediate consumption), and c_k is the external (final) consumption for industry k's output. The intermediate consumption, z_{kr}, is assumed to be proportional to the output of industry r $(r \in \{1,...,K\} \text{and } r \neq k)$, expressed as $z_{kr} = a_{kr}x_r$. In the common form of the Leontief I-O model, industry production is modeled as $\mathbf{x} = Ax + \mathbf{c}$, where $\mathbf{x}$ is the vector of industry production outputs, $\mathbf{A}$ is an industry-by-industry matrix of interdependency coefficients, a_{kr} (proportion of industry k's input to r, with respect to total production of industry r), and $\mathbf{c}$ is a vector of final consumption. The model shows that total production is made up of industry-to-industry intermediate production, $\mathbf{Ax}$, and production to satisfy final consumption, $\mathbf{c}$.

The availability of data describing the parameters of the I-O model in the US through the Bureau of Economic Analysis (BEA) (2010), as well as a number of other countries [OECD 2012], justifies the extensive use of I-O models. To model the propagation of inoperability, or the proportional extent to which industries are unproductive after a change in final consumption or a forced change in final consumption due to a lack of supply, Santos and Haimes (2004) propose the Inoperability Input-Output Model (IIM), extending the capability of the I-O model to model not only economic interdependency but interdependency in broader infrastructure sectors. This risk-based model is defined from two metrics [Haimes et al., 2005, Santos 2006]: (i) inoperability q_k and (ii) final consumption perturbation $c_k^\star$, which are defined in Eqs. (4) and (6), respectively. Providing a different perspective from the traditional I-O model, the IIM shows how normalized production losses propagate through interconnected industries with a normalized interdependency matrix $\mathbf{A}^\star$. Describing the relationships among K industries, resulting in matrices of size $K \times K$ and vectors of length K, Eq. (3) formulates the propagation of the inoperability in a group of interconnected industries.

$$\mathbf{q} = \mathbf{A}^\star\mathbf{q} + \mathbf{c}^\star \Rightarrow \mathbf{q} = [\mathbf{I} - \mathbf{A}^\star]^{-1}\mathbf{c}^\star \tag{3}$$

Vector $\mathbf{q}$ 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. (4), 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 represents the situation in which an industry is completely inoperable.

$$q_k = (\hat{x}_k - \tilde{x}_k)/\hat{x}_k \Leftrightarrow \mathbf{q} = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}(\hat{\mathbf{x}} - \tilde{\mathbf{x}}) \tag{4}$$

A normalized form of the original $\mathbf{A}$ matrix describing the extent of interdependence among a set of industries or sectors is defined as $\mathbf{A}^\star$. The row elements of $\mathbf{A}^\star$ indicate the proportion of additional inoperability that are contributed by a column industry to the row industry, shown in Eq. (5),

$$a_{rk}^\star = a_{rk}(\hat{x}_r/\hat{x}_k) \Leftrightarrow \mathbf{A}^\star = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}\mathbf{A}[\mathrm{diag}(\hat{\mathbf{x}})] \tag{5}$$

The calculation of $\mathbf{c}^\star$, a vector of normalized final consumption reduction is provided in Eq. (6), where the elements of $\mathbf{c}^\star$ represent the difference in as-planned final consumption $\hat{c}_k$ and perturbed final consumption $\tilde{c}_k$ divided by as-planned production, quantifying the reduced final consumption for industry k as a proportion of total as-planned output.

$$c_k^\star = (\hat{c}_k - \tilde{c}_k)/\hat{x}_k \Leftrightarrow \mathbf{c}^\star = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}(\hat{\mathbf{c}} - \tilde{\mathbf{c}}) \tag{6}$$

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.

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);Resurreccion and Santos (2013); Pant et al., (2011); Haggerty et al., (2008); Lian and Haimes (2006)). However, some (e.g., Kujawski (2006);Kelly (2015); Kujawski (2006); Kelly (2015)) have questioned the usefulness (and theoretical plausibility) of supply-driven models developed from concepts by Ghosh (1958). 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 $N^{\bar{\alpha}}$ represents the set of nodes outside of the area of interest, such that $N = N^{\alpha} \cup N^{\bar{\alpha}}$. 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.

2.2.1. 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. (7), 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 $\sum_{i \in (N_+^{\prime\alpha} \cap N_k^{\prime})} S_i^k$, where $N_+^{\prime\alpha}$ represents the set of nodes that are home to suppliers in the region of interest α after the disruption, as shown in Eq. (8). 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. (9), 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.

$$\hat{c}_k = (\hat{c}_k)_{int} + (\hat{c}_k)_G, \quad k \in \{1, \ldots, n\} \tag{7}$$

$$\hat{c}_k - \tilde{c}_k = \sum_{i \in (N_+^{\prime\alpha} \cap N_k^{\prime})} S_i^k, \quad k \in \{1, \ldots, n\} \tag{8}$$

$$c_k^{\star} = \frac{\sum_{i \in (N_+^{\prime\alpha} \cap N_k^{\prime})} S_i^k}{\hat{x}_k}, \quad k \in \{1, \ldots, n\} \tag{9}$$

2.2.2. 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 $\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} - b_i^k$ 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 $\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} S_i^k$. 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.

$$\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} S_i^k = \Delta\hat{x}_k + \Delta(\hat{c}_k)_{int}, \quad k \in \{1, \ldots, n\} \tag{10}$$

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. (4) with $\Delta\hat{x}_k/\hat{x}_k$. Also, internal consumption failure, as shown in Eq. (7), 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. (6) 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. (11). For the industries experiencing difficulties only in importing their required commodities, there exists a final consumption perturbation, as modeled in Eq. (12).

$$\frac{\Delta\hat{c}_k}{\hat{x}_k} = \frac{\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} S_i^k - \Delta\hat{x}_k}{\hat{x}_k}, \quad k \in \{1, \ldots, n\} \tag{11}$$

$$c_k^{\star} = \frac{\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} S_i^k}{\hat{x}_k} - q_k, \quad k \in \{1, \ldots, n\} \tag{12}$$

Eqs. (9) and (12) combined with the IIM in Eq. (3) 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. (9) and (12) 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. (13).

$$c_k^{*} = \frac{\sum_{i \in (N_+^{\prime\alpha} \cap N_k^{\prime})} S_i^k}{\hat{x}_k} + \frac{\sum_{i \in (N_-^{\prime\alpha} \cap N_k^{\prime})} S_i^k}{\hat{x}_k} - q_k, \quad k \in \{1, \ldots, n\} \tag{13}$$

Any of Eqs. (9), (12), or (13) captures the perturbation vector $\mathbf{c}^{\star}$ that parameterizes the interdependency model in Eq. (3) 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.

2.3. 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. (3), 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. (14) and (15) are two such metrics motivated by Eq. (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. (14) 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.

$$Я_e^k = \frac{Q_e^k - Q_R^k}{Q_e^k} \tag{14}$$

For a perspective that spans all industries, Eq. (15) 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.

$$Я_e^R = \frac{Q_e - Q_R}{Q_e} \tag{15}$$

Assuming a multi-industry perspective and considering a hypothetical decision maker interested in limiting economic losses across multiple industries, Eq. (15) serves as the objective function in the following optimization framework that integrates the multi-commodity network flow model from Section 2.1 and the Inoperability Input-Output Model from Section 2.2. Following a particular disruption e that affects a particular set of transportation links, the proposed model in Eqs. (16)–(24) 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);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	$N_-'^{\alpha}$	set of nodes that are home to consumers in the region of interest α
N_+'	set of nodes that are home to suppliers	$N_+'^{\alpha}$	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	$b_i'^k$	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_i^k	slack variable that captures undelivered commodity k remaining with the supplier node i or unsatisfied demand at demand node i
$a_{rk}^{\star}$	elements of the normalized interdependency matrix $\mathbf{A}^{\star}$	$c_k^{\star}$	final consumption perturbation for industry k
x_k	production level of industry k in monetary value		

Decision variable

$f_{ij}'^k$	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.

$$\max Я_e^R \tag{16}$$

$$\text{s.t.} \sum_{k=1}^{K} f_{ij}'^k \le u_{ij}', \quad \forall\ (i, j) \in L' \tag{17}$$

$$\sum_{(i,j)\in L'} f_{ij}'^k - \sum_{(j,i)\in L'} f_{ji}'^k + \gamma_i S_i^k = b_i'^k, \quad \forall\ k = 1,\ ...,K \tag{18}$$

$$\gamma_i = \begin{cases} -1 & \text{for } i \in N_-' \\ +1 & \text{for } i \in N_+' \\ 0 & \text{for } i \in N_0' \end{cases} \tag{19}$$

$$c_k^{\star} = \frac{\sum_{i\in(N_+'^{\alpha}\cap N_k')} S_i^k}{\hat{x}_k} + \frac{\sum_{i\in(N_-'^{\alpha}\cap N_k')} S_i^k}{\hat{x}_k} - \mu_k q_k, \quad \forall\ k = 1,\ ...,K \tag{20}$$

$$\frac{1}{M} \sum_{i\in(N_-'^{\alpha}\cap N_k')} S_i^k \le \mu_k \le M \sum_{i\in(N_-'^{\alpha}\cap N_k')} S_i^k, \quad \forall\ k = 1,\ ...,K \tag{21}$$

$$\begin{bmatrix} q_1 \\ \vdots \\ q_K \end{bmatrix} = \begin{bmatrix} a_{11}^{*} & \cdots & a_{1K}^{*} \\ \vdots & \ddots & \vdots \\ a_{K1}^{*} & \cdots & a_{KK}^{*} \end{bmatrix} \begin{bmatrix} q_1 \\ \vdots \\ q_K \end{bmatrix} + \begin{bmatrix} c_1^{\star} \\ \vdots \\ c_K^{\star} \end{bmatrix} \tag{22}$$

$$Q_R = \sum_{k=1}^{K} x_k q_k \tag{23}$$

$$f_{ij}'^k \in Z,\ \ \forall\ (i, j) \in L',\ k = 1,...,K$$
$$\mu_k \in \{0,1\}, \quad \forall\ k = 1,...,K \tag{24}$$

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. (17) 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. In other words, all industries share the capacity of network components, resulting in competition among them for a share of undisrupted capacity. $f_{ij}'^k$ represents the flow of commodity k across link (i, j) which remains in the updated set of links, L'. Eq. (18) represents mass balances on each node, where $b_i'^k$ 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. (19). Eqs. (20)-(22) 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. (13) 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. (20), 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 $N_+'^{\alpha}$, and unmet demand at demand nodes within the region of interest represented by $N_-'^{\alpha}$ A binary coefficient, μ_k, in Eq. (20) 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. (21) requires that μ_k be binary, defining a sufficiently large M. Eq. (22) 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. (23) with total economic loss Q_R. This equation integrates the monetary value of the flow of each industry into the objective function. The objective function aims to maximize the progress in reducing economic loss, and as the structure of the network does not let the improvement in all industries flow at once, the objective function prioritizes the commodities that most affect the reduction in economic loss. And the objective function is the proportional economic saving, parametrized based on Eq. (15) 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 2.1. and 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);Lee et al., (2007); Holden et al., (2013)).

The complexity of the model is $O(n^2K)$, and it has $O(K)$ binary variables. We do note that although complexity of the problem is linear, but the number of industries would not be drastically large, meaning that the number of constraints would be computationally manageable. However, as the network flow variables are defined as integer, $O(n^2)$, the increase in the size of the network, combined with the number binary variables, complicates the calculations for large instances. In the stylized case study in the next section, the model performs well for small to medium scale problems, and the average solution time is less than 5 s. Also, it is possible to enhance the performance of the formulation for large scale problems by relaxing the integrality of the network variables.

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 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. This illustrative network is adapted from Darayi et al., (2017). The case study has been solved using optimization software LINGO, version 15.

3.1. Supply-demand network

Fig. 4 depicts a supply-demand network considering supply nodes as the three important business economic areas within the state of Oklahoma, consisting of Oklahoma City (node 1), the Port of Catoosa in Tulsa (node 2), and the Port of Muskogee (node 3). Customers (demand nodes) in the most important states interacting with Oklahoma industries are Texas, Louisiana, Arkansas, and Illinois [Ingalls et al., 2002].

The multi-modal freight transportation network, which enables the commodity flows from suppliers within the state of Oklahoma to the out of state consumers, is discussed in brief in Table 1. 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 enable trade 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. In addition to the truck way facilities, an intermodal rail-truck facility in Oklahoma City near the junction of I-35 and I-40, and the one in Tulsa, OK, which run by Burlington Northern Santa Fe (BNSF) railroad are considered in developing the network, as well as part of the inland waterway network navigated by McClellan–Kerr Arkansas River Navigation System which 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).

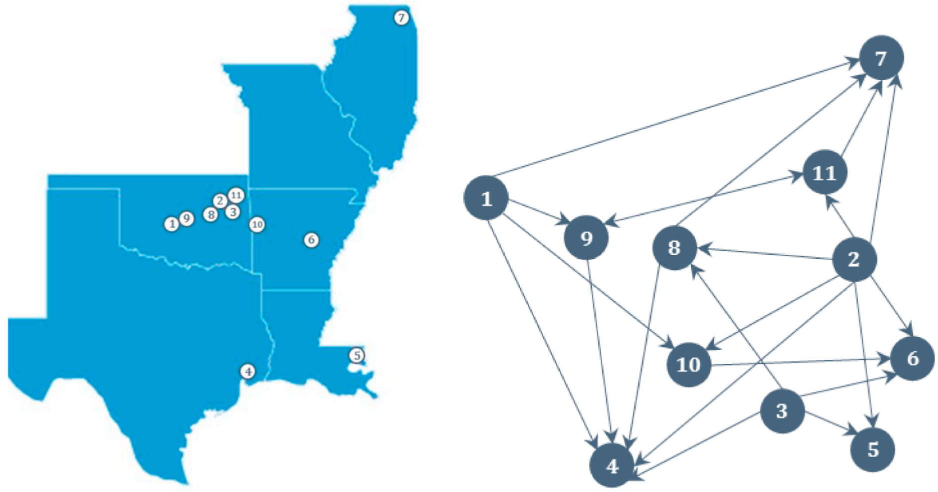
As defined by NAICS, 62 industries operate in Oklahoma, therefore the $\mathbf{A}^{\star}$ matrix regionalized for Oklahoma is 62×62. Due to high trade figures reported by Bureau of Transportation Statistics (2010a), six industries are considered to be industries that primarily export commodities to out-of-state customers, listed in Table 2. Discussed previously, it is assumed that each commodity belongs to an industry as defined by NAICS economic sectors, and each node within the network is considered to be home to either suppliers or consumers of multiple commodities.

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 3 (assuming constant monthly demand, or annual demand divided by 12).

3.2. Freight movement and disruption

To parametrize the MCNF model in Eq. (1), 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 A1 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 3, 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 one-at-a-time 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, two transshipment nodes (nodes 9 and 11, which have a vital role in connecting segments of high volume freight traffic on interstate highways), some segments of the North America Railroad (node 8 and link (8-4)), a local railroad which connects industrial parks to the North America railroad (link (2–8)), and parts of the waterway system (link (2–5)) were each removed one-at-a-time from the network to define the disruption scenarios. And the impact of these individual removals were measured. 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



(a) (b)

Fig. 4. Representations of (a) spatial location of multi-modal nodes in Oklahoma and surrounding states, and (b) the connected transportation network.

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 reports $\sum_{i \in (N_+^{\prime\alpha} \cap N_k)} S_i^k$, 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, 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 2
Names and NAICS codes for the primary 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

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. (14). Other industries within the state will be affected by the interdependent effect of this failure, as captured by q^k in Eq. (3), 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, demand perturbation is calculated with Eq. (14). Resulting industry inoperability, q^k, is provided in Table 5 and depicted in Fig. 5. 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

Table 1
Spatial location of multi-modal nodes in Oklahoma and surrounding states.

Component	Description
Node 1	Oklahoma City
Node 2	Port of Catoosa
Node 3	Port of Muskogee
Node 4	Port of Texas City
Node 5	Port of New Orleans
Node 6	Port of Little Rock
Node 7	Port of Chicago
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 which connects Oklahoma City, OK, with Chicago, IL.
Link (2,8)	A local railroad connecting Port of Catoosa to the North America railroad
Link (1,4)	Part of the North America railroad which 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 truck way connects Oklahoma City to Texas City, TX, using interstate highways I-35 and I-45.
Link (9,11)	Part of interstate highway I-44 which connects Oklahoma City to Tulsa.

Table 3
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

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. The inoperability values in Table 5 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).

Considering each industry's production level in monetary value and calculating total impact of the disruption across the state's industries with Q, Table 6 and Fig. 6 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.

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, Tables 7 and 8 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. (16)–(24) 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 $\text{Я}_e^R = 0$ 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 Figs. 7 and 8 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.

Fig. 7 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 8, 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 of the collective industries, as measured by Я_e^R, by more than 37%. As shown in Table 8, 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%.

As a contingent rerouting strategy is sought considering the total economic impact embedded in Eq. (15), priorities given to high-dollar industries and those with the highest interdependent impacts across industries. Though Fig. 8 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. Because of the structure of the network in the case study, the assumption that the residual capacity in all industries should be less than or equal to its inoperability results in infeasibility as (i) the distribution of the network capacity over the network component does not allow the flow in all industries to increase at once, and (ii) the objective function tries to maximize the total economic loss in the minimum possible time immediately after disruptions, and as such it focuses on rerouting the flow of those industries most affect reducing total economic loss. These results can also assist in prioritizing more important industries in after a disruption.

Fig. 9 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 Fig. 9, because optimal contingency rerouting tends not to benefit these industries in favor of the larger economy, as shown in Fig. 8.

Table 4
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

Table 5
Industry inoperability across six most important industries within the state of Oklahoma.

Removed component	Industry					
	Food and beverage	Petroleum and coal	Chemical products	Nonmetallic mineral	Machinery mfg.	Misc. mfg.
Node 9	0	9.00E-04	4.90E-03	0	0	1.50E-03
Node 8	0	1.16E-02	9.00E-04	1.20E-03	1.60E-03	8.00E-04
Node 11	0	9.00E-04	3.80E-03	0.00E+00	0	1.00E-04
Link (1,7)	0	1.00E-04	2.00E-04	8.90E-03	1.00E-04	4.50E-03
Link (9,11)	0	9.00E-04	3.80E-03	0	0	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	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

4. Concluding remarks

With regard to the three components of resilience capacity identified by Vugrin and Camphouse (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, (ii) defining a measure of adaptive capacity to valuate rerouting strategies, and (iii) the model incorporates the economic elements to study the disruption effects on the infrastructure networks from other perspectives. The results provide insight to decision makers about the behavior of each commodity such that they may adapt policies aligned with the behavior of the model (e.g., allocating emergency warehouses for commodities whose economic loss increases after implementing the adaptive capacity approach). Further, 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

Table 6
Economic losses, in million USD, 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

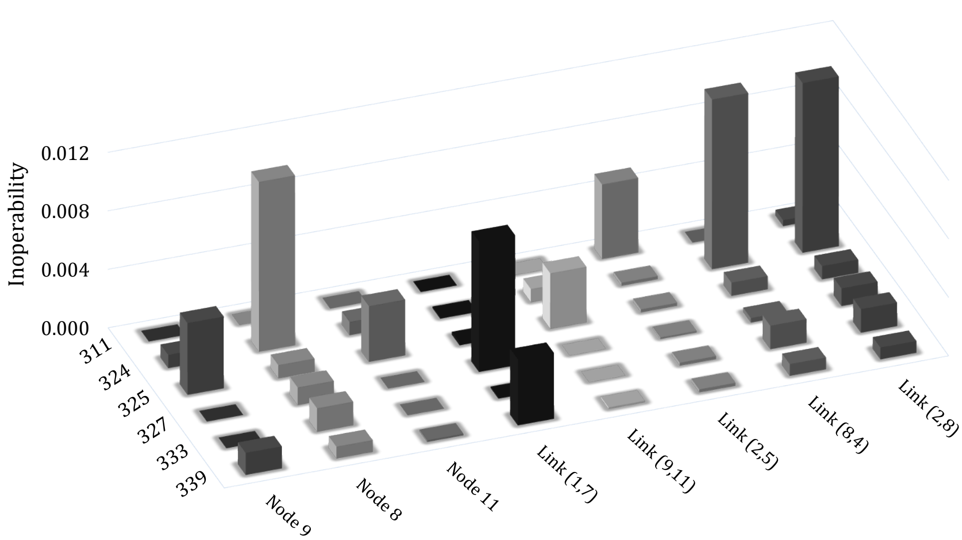


Fig. 5. Graphical depiction of industry inoperability resulting from network component removal.

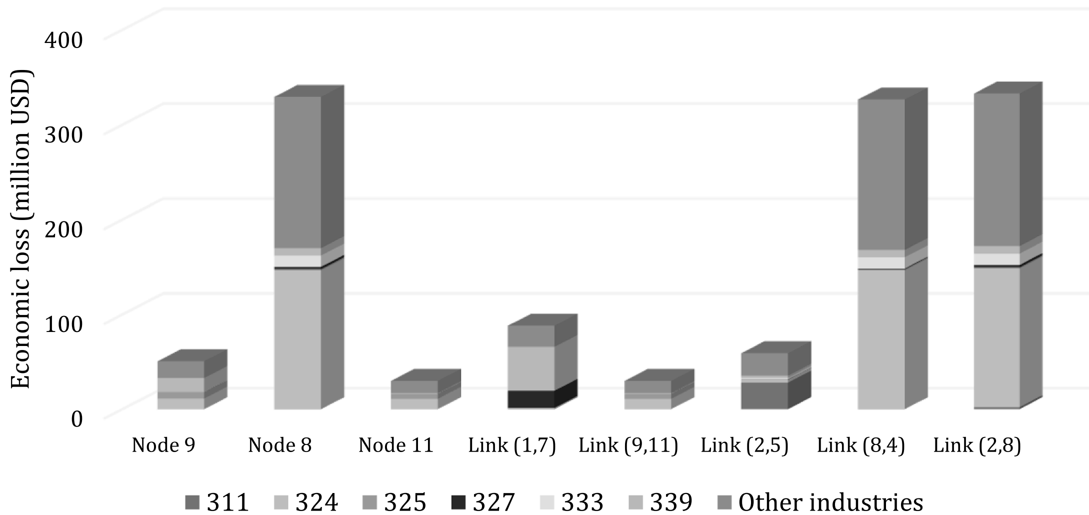


Fig. 6. Interdependent economic losses in Oklahoma due to network component removal.

Table 7
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	4.80E-03	0	0	0
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	4.70E-03	0	0	0
Link (1,7)	0	0	1.00E-04	7.50E-03	0	1.00E-04
Link (9,11)	2.00E-04	0	3.60E-03	0	0	0
Link (2,5)	0	1.00E-04	1.50E-03	0	2.00E-04	0
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

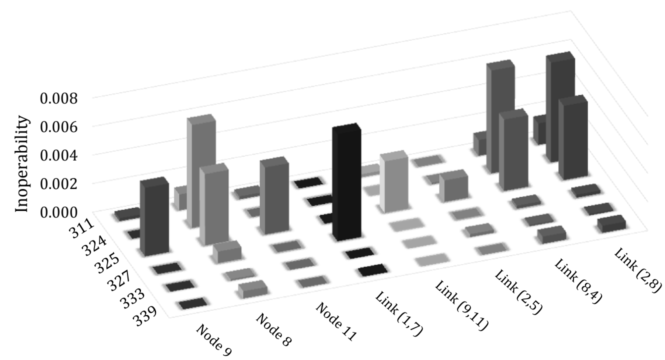


Fig. 7. Economic inoperability caused by the disruption devising a contingent rerouting.

Table 8
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

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%. The ultimate usefulness of such a model could lie in (i) assisting transportation planners in effective rerouting that minimizes impacts to certain industries, and (ii) assisting decision makers in those industries how certain disruptions and resulting adaptive planning may impact their company when certain commodities do not arrive as planned. 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.

The real-world application of this work lies in informing a central planner/policy maker to devise contingent rerouting strategies more effectively to enhance the resilience of freight movement to maintain the continuity of service for businesses using the multi-modal transportation network. For example, in the case of a natural hazard that affects the Port of Catoosa, one of the most important business economic areas in Oklahoma, such a central decision maker could be represented by the nine-member board that oversees the port [Business View Magazine 2016]. These results suggest that it may be economically beneficial for policy makers to explore ways to reroute the commodity flow by facilitating contingent rerouting or incentivizing companies to move commodities through alternative transportation modes in case of a disruption to port dock operations. The proposed model helps decision makers to prioritize the affected industry sectors when devising contingent rerouting strategies to facilitate the flow of commodities during the disruption. For example, *Miscellaneous manufacturing* and *Machinery* freight are handled at the General Dry Cargo dock, which handles the largest tonnage in the port. Hence, these sectors would be vulnerable to any disruption that threatens the functionality of the General Dry Cargo dock for the real-world operations of the port. Similarly, any disruptions threatening the operations at Liquid Bulk and Grains docks would interrupt the flow of *Chemical products* and *Food and beverage and tobacco products*, respectively. The Port of Catoosa is a major industrial hub in the Tulsa metropolitan statistical area, which contributes to 33.4% of the State of Oklahoma's economy [Tulsa Regional Chamber 2018], hence the options here are aimed at benefiting the wider state economy through the port. The insights gained from this paper can lead to better risk management strategies to mitigate the effect of a multi-modal freight transportation disruption.

This initial formulation can be further improved by accounting for

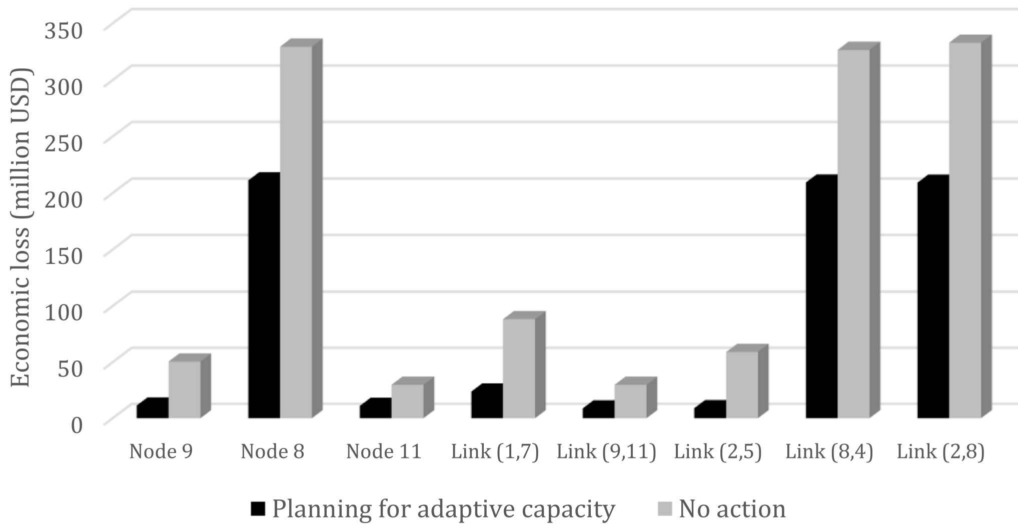


Fig. 8. Total economic loss across all industries in Oklahoma, contingent rerouting versus no action.

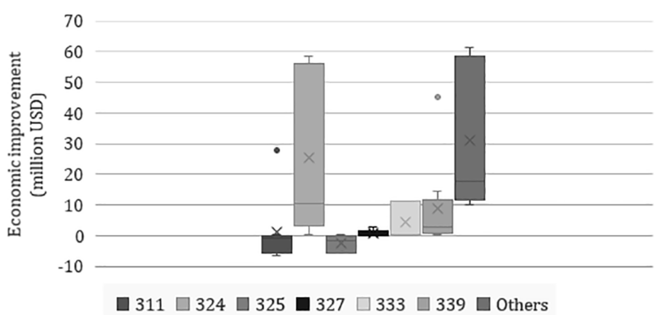


Fig. 9. Effects of contingent rerouting on different industries.

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. Further, the proposed integrated framework could be extended to study the *design of a resilient freight network* considering uncertain disruptions of multiple components (e.g., Alderson et al., (2013);Alderson et al., (2013)).

Acknowledgments

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Appendix

Table A1
Link capacities among the origin/destination nodes in the illustrative network (in tons) [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		

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