Economic Impacts of Multi-Modal Transportation Network Recovery

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SPTC17.1-03-F

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TECHNICAL REPORT DOCUMENTATION PAGE

1. REPORT NO.	2. GOVERNMENT ACCESSION NO.	3. RECIPIENTS CATALOG NO.
SPTC17.1-03-F		

4. TITLE AND SUBTITLE Economic Impacts of Multi-Modal Transportation Network Recovery	5. REPORT DATE October 15, 2018 6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S) Kash Barker	8. PERFORMING ORGANIZATION REPORT
9. PERFORMING ORGANIZATION NAME AND ADDRESS School of Industrial and Systems Engineering The University of Oklahoma 202 W. Boyd St., Rm. 124 Norman, OK 73019	10. WORK UNIT NO. 11. CONTRACT OR GRANT NO. DTRT13-G-UTC36
12. SPONSORING AGENCY NAME AND ADDRESS Southern Plains Transportation Center 201 Stephenson Pkwy, Suite 4200 The University of Oklahoma Norman, OK 73019	13. TYPE OF REPORT AND PERIOD COVERED Final October 15, 2017 – May 1, 2018 14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES
University Transportation Center

16. ABSTRACT

Recent US planning documents focus on transportation network preparedness, emphasizing “securing and managing flows of people and goods” along transportation networks. Presidential Policy Directive 21 states that critical infrastructure “must be secure and able to withstand and rapidly recover from all hazards.” This combination of the abilities to (i) withstand the effects of a disruption and (ii) recover timely is often referred to as resilience. In a recently completed SPTC project, we examined transportation network component importance from the perspective of the vulnerability of commodity flows and the interdependent, multi-regional, multi-industry impact of the disruption of those commodity flows. Naturally a more comprehensive view of transportation network resilience must extend from the vulnerability of transportation assets to their post-disruption recovery. In this project report, we build upon the prior SPTC project to propose an optimization formulation to recover disrupted components in the multi-modal transportation network with multi-industry impacts in mind. The primary contribution of this work is the relating network recoverability and interdependent impact to individual network components – an important perspective not currently available in the literature. That is, how can the complementary view of economic impact assist transportation planners in understanding (i) what order of components to repair and (ii) how to schedule work crews to perform this repair?

17. KEY WORDS	18. DISTRIBUTION STATEMENT
Recovery, Resilience, Economic impact, Commodity flows, Multi-regional, Planning	No restrictions. This publication is available at www.sptc.org and from the NTIS.

19. SECURITY CLASSIF. (OF THIS REPORT)	20. SECURITY CLASSIF. (OF THIS PAGE)	21. NO. OF PAGES	22. PRICE
Unclassified	Unclassified	38	

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 03)

ECONOMIC IMPACTS OF MULTI-MODAL TRANSPORTATION NETWORK RECOVERY

Final Report
October 15, 2018

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EXECUTIVE SUMMARY

Among the critical infrastructures defined by the US government are transportation networks, which are vital to a society and subject to natural hazards, human-made events, or common failures. The ultimate usefulness of understanding transportation network disruptions is not just a descriptor of physical damage, but of economic interruption due to infrastructure inoperability. As such, discussions of transportation network recovery should account for multi-industry impacts.

In a recently completed Southern Plains Transportation Center (SPTC) project, we examined transportation network component importance from the perspective of the vulnerability of commodity flows and the interdependent, multi-regional, multi-industry impact of the disruption of those commodity flows. If *resilience* is defined to be the combination of a system's ability to (i) withstand the effects of a disruption (or minimal vulnerability) and (ii) recover timely (or enhanced recoverability), then naturally a more comprehensive view of transportation network resilience must extend from the vulnerability of transportation assets to their post-disruption recovery.

In this report, we build upon the prior SPTC project to propose an optimization formulation to *recover* disrupted components in the multi-modal transportation network with multi-industry impacts in mind. The primary contribution of this work is the relating network recoverability and interdependent impact to individual network components – *an important perspective not currently available in the literature*. That is, how can the complementary view of economic impact assist transportation planners in understanding (i) what order of components to repair and (ii) how to schedule work crews to perform this repair? This could assist local municipalities for short-term recovery actions (e.g., debris removal) and state-level entities for long-term actions (e.g., rebuilding damaged assets).

Several reasons make this work important to the region, including: (i) Oklahoma's central role in transporting goods via a multi-modal transportation network (interstate highways, railways, and inland waterways), and (ii) as the multi-modal networks are prone to disruption and delay (and will only continue to do so as long-term climate related degradation can lead to more disruptions under smaller scale disasters), understanding the role of recovering individual links in regional economic productivity is important.

It is recommended that the Oklahoma Department of Transportation consider the models provided in this report to supplement and complement existing approaches when considering investments to recover disrupted components of the multi-modal transportation infrastructure in the state. The methods proposed in this report are illustrated with data-driven studies from Oklahoma, though they are at levels of granularity that may not be directly conducive to investments about specific components (e.g., a particular bridge).

1. INTRODUCTION

Freight transportation infrastructure, including ports, intermodal stations, interstate highways and railways, is a quickly growing part of productivity of industries in the US due to its support of regional and national economy. In recent decades, the operability of freight transportation infrastructure has been threatened by numerous disruptive events, whether natural hazards, human-made events, or common failures. And all of these disruptions interrupted commodity flows throughout the affected regions and adversely impacted economic productivity. Many recent large-scale examples highlight the growing need to deal with disruptions: the great Mississippi and Missouri flood in 1993 caused delays and cancelations for several railroad segments[1]; Hurricane Katrina in 2005 adversely impacted the infrastructure system, along with economic productivity, in Louisiana, Mississippi, and Alabama[2]; and Hurricane Sandy affected the East Coast from Florida to Maine, disabling transportation networks including roads, public transit, port terminal facilities, and the harbor in the New York/ New Jersey area[3].

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)[4] was established to focus national efforts to enhance the critical infrastructure network resilience. In many U.S. preparedness planning documents, resilience is defined as the ability of the network to withstand, adapt, and recover from disruptive events[5]. Based on Barker et al.[6], network resilience can be defined as two fundamental dimensions: (i) *vulnerability*, or the lack of ability of a network to withstand disruptive events and maintain its maximum possible level of performance in the immediate aftermath of disruptions, and (ii) *recoverability*, or the ability of the network to return to a desired level of performance within a recovery time horizon. These two dimensions describe similar components of *robustness* and *rapidity* in the resilience triangle literature[7]. Similarly, Vugrin and Camphouse[8] define the resilience capacity of a system as a function of three capacities: (i) *absorptive capacity,* or to the extent a network is able to 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. The combination of absorptive and adaptive capacities can be thought of as analogous to reducing vulnerability, and restorative capacity is analogous to recoverability[9]. Figure 1 highlights the relationship between (i) vulnerability and recoverability and (ii) absorptive, adaptive, and restorative capacities.

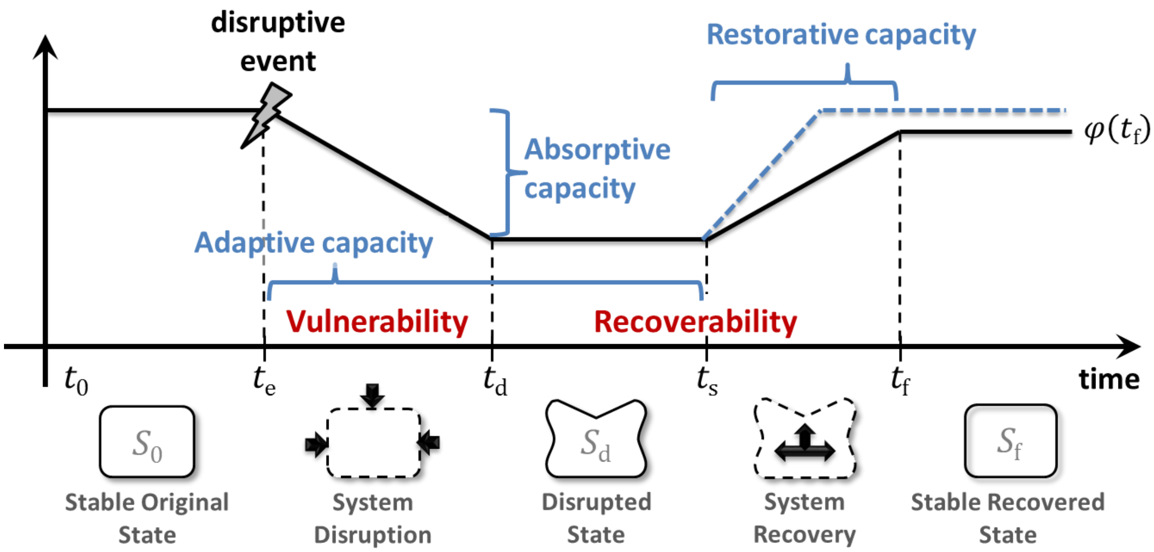


Figure 1. Enhancing network resilience via restorative capacity $\varphi(t)$.

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.[10] 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.[11] 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.[12] expand the model by Nurre et al.[10] to recover interdependent infrastructure networks. In terms of optimizing network connectivity, Aksu and Ozdamar[13] formulate a multi-vehicle problem to recover blocked links that are critical for maintaining network connectivity under limited recovery resources. Celik et al.[14] also plan debris cleaning processes with the aim of recovering transportation network connectivity under uncertain nature of the problem. Kasaei and Salman[15] 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 enable 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[16]. This is depicted graphically in Figure 2 and mathematically in Eq. (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 $(\%\Delta DY^{\max} - \%\Delta DY)$ after a disruption. 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[17]-[21]. 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 subsequently, 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.

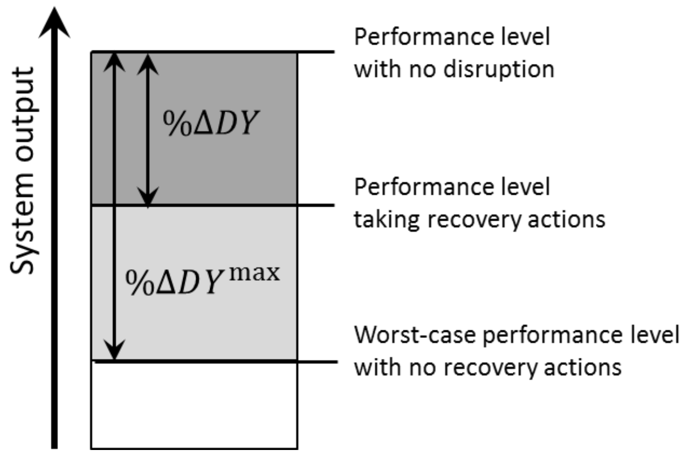


Figure 2. The performance components of restorative capacity (adapted from [22]).

$$\text{restorative capacity} = \frac{\%\Delta \mathrm{DY}^{\max} - \%\Delta \mathrm{DY}}{\%\Delta \mathrm{DY}^{\max}} \tag{1}$$

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[16],[22],[23]. The proposed optimization model is developed following a three-step approach, as illustrated in Figure 3.

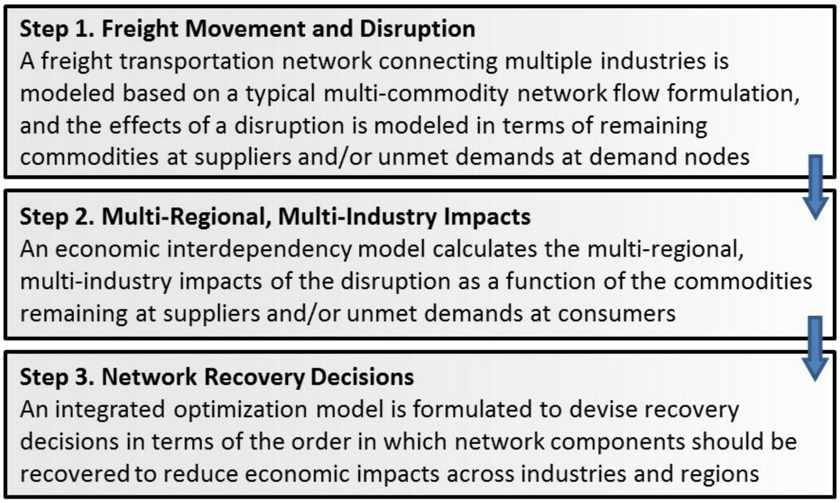


Figure 3. Three-step approach to devise network recovery with multi-regional, multi-industry impacts.

2.1. STEP 1: FREIGHT MOVEMENT AND DISRUPTION

The multi-modal freight transportation network of interest in this work will be modeled with a typical multi-commodity network flow (MCNF) problem. MCNF problems, which minimize the cost of the flow of multiple commodities across a capacitated network of supply and demand nodes, arise in a wide variety of applications, including telecommunications[24], warehousing[25], and multi-modal transportation networks[26],[27], among others.

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, each of which could be home to either suppliers or consumers of multiple commodities (*K*), or just an intermediate node, and a set of links, L, is formulated in Eq. (2). 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 Eq. (2), 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.

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

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.

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, as calculated in Eq. (1). 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. There are multiple sets of commodities, and it is assumed that each set 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. STEP 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[28], a linear model of the commodity flows in a set of interconnected industries. This section provides 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.

2.2.1. Input-Output Model and its Multi-Regional Extension

The input-output model has been widely accepted as a useful model for analyzing the interdependent connections among industries[29], and the use of the input-output enterprise for studying disruptions was among the *10 Most Important Accomplishments in Risk Analysis: 1980-2010*[30]. In the traditional input-output model[28], the entire economy is considered as a group of n interacting industries, each producing a single commodity. Under a static equilibrium, the total output of industry (or economic sector) k is distributed (i) to other industries for use as input to production and (ii) to final consumers to satisfy external (consumption) demand. Under a proportionality assumption, this equilibrium condition is described with $x_k = \sum_{h=1}^{K} z_{kh} + c_k$, where x_k is the total output of industry k, z_{kh} is the input of industry k to the production of industry h (intermediate consumption), and c_k is the external (final) consumption for industry k's output. The intermediate consumption, z_{kh}, is assumed to be proportional to the output of industry h ($h \in \{1, \dots, K\}$ and $h \neq k$), expressed as $z_{kh} = a_{kh}x_h$. The common form of the Leontief input-output model is expressed in Eq. (3), where $\mathbf{x}$ is an $n \times 1$ vector of industry production outputs, a_{kh} is proportion of industry k's input to h, with respect to total production of industry h (which form $n \times n$ industry-by-industry matrix of interdependency coefficients $\mathbf{A}$), and $\mathbf{c}$ is an $n \times 1$ vector of final consumption. The model shows that total production is made up to satisfy industry-to-industry intermediate production ($\mathbf{Ax}$) and final consumption ($\mathbf{c}$).

$$x_k = \sum_{h=1}^{K} z_{kh} + c_k \Rightarrow \mathbf{x} = \mathbf{Ax} + \mathbf{c} \Rightarrow \mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{c} \tag{3}$$

The traditional input-output model has been extended to represent multi-regional economic interdependency[29]. A regional input-output matrix $\mathbf{A}^r$ is developed by modifying the elements of the $\mathbf{A}$ matrix. As shown in Eq. (4), l_k^r, referred to as a location quotient, is defined to indicate how well industry k's production satisfies the regional demand.

$$a_{kh}^r \begin{cases} l_k^r a_{kh}, & l_k^r < 1 \\ a_{kh}, & l_k^r \geq 1 \end{cases} \tag{4}$$

The location quotient, l_k^r, is mathematically defined in Eq. (5), 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.

$$l_k^r = \frac{x_k^r / x_{\text{total}}^r}{x_k / x_{\text{total}}} \tag{5}$$

As discussed by Isard et al.[31], 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 k 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. (6).

$$a_{kh}^{rr'} = \frac{z_k^{rr'}\, z_{kh}^{r'}}{\xi_k^{r'}\, x_h^{r'}} = \psi_k^{rr'} a_{kh}^{r'} \tag{6}$$

Ultimately, an inter-regional input-output model is proposed in Eq. (7), the details of which can be found in Isard et al.[31] and Miller and Blair[29].

$$x_k^r = \sum_{r'=1}^{R}\sum_{h=1}^{K} \psi_k^{rr'} a_{kh}^{r'} x_h^{r'} + \sum_{r'=1}^{R} \psi_k^{rr'} c_k^r \tag{7}$$

The multi-regional, multi-industry input-output model is provided in Eq. (8). Each sub-matrix $\mathbf{\Psi}^{rr'}$ 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 $\mathbf{\Psi}^{rr'}$, 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[32].

$$\begin{bmatrix} x^1 \\ \vdots \\ x^R \end{bmatrix} = \begin{bmatrix} \Psi^{11} & \cdots & \Psi^{1R} \\ \vdots & \ddots & \vdots \\ \Psi^{R1} & \cdots & \Psi^{RR} \end{bmatrix} \begin{bmatrix} A^1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & A^R \end{bmatrix} \begin{bmatrix} x^1 \\ \vdots \\ x^R \end{bmatrix} + \begin{bmatrix} \Psi^{11} & \cdots & \Psi^{1R} \\ \vdots & \ddots & \vdots \\ \Psi^{R1} & \cdots & \Psi^{RR} \end{bmatrix} \begin{bmatrix} c^1 \\ \vdots \\ c^R \end{bmatrix} \tag{8}$$

2.2.2. Inoperability Input-Output Model and its Multi-Regional Extension

While the input-output model describes the connections between the interdependent industries in terms of commodity exchange, Santos and Haimes[17] developed an extension, the Inoperability Input-Output Model (IIM), to represent how a proportional disruption propagates through interconnected industries. The IIM is defined based on two metrics to assess the risk of disruptions in infrastructure networks[33],[34]: (i) inoperability for industry k, q_k, defined as the extent to which industries are unproductive, and (ii) final consumption perturbation $c_k^\star$. The IIM shows how normalized production losses propagate through interconnected industries with a normalized interdependency matrix $\mathbf{A}^\star$. As formulated in Eq. (9), the IIM describes relationships among K industries, and models the propagation of the inoperability in a group of K interconnected industries.

$$\mathbf{q} = \mathbf{A}^\star\mathbf{q} + \mathbf{c}^\star \Rightarrow \mathbf{q} = [\mathbf{I} - \mathbf{A}^\star]^{-1}\mathbf{c}^\star \tag{9}$$

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. (10), 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.

$$q_k = (\hat{x}_k - \tilde{x}_k)/\hat{x}_k \iff \mathbf{q} = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}(\hat{\mathbf{x}} - \tilde{\mathbf{x}}) \tag{10}$$

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. (11).

$$a_{hk}^{\star} = a_{hk}(\hat{x}_h/\hat{x}_k) \iff \mathbf{A}^{\star} = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}\mathbf{A}[\mathrm{diag}(\hat{\mathbf{x}})] \tag{11}$$

Final consumption perturbation for industry k, $c_k^{\star}$, represents the change in final consumption for industry k due to disruptive events. The calculation of $\mathbf{c}^{\star}$, a vector of normalized final consumption reduction is provided in Eq. (12), 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. It quantifies the reduced final consumption for industry k as a proportion of total as-planned output.

$$c_k^{\star} = (\hat{c}_k - \tilde{c}_k)/\hat{x}_k \iff \mathbf{c}^{\star} = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}(\hat{\mathbf{c}} - \tilde{\mathbf{c}}) \tag{12}$$

Crowther and Haimes[35] followed the same principles in developing multi-regional input-output model to propose the Multi-Regional Inoperability Input-Output Model (MRIIM) by integrating Eqs. (8) and (9). In the MRIIM, provided in Eq. (13), each of the $K \times K$ sub-matrices $\mathbf{\Psi}^{\star rr'}$, $\forall\, r, r' \in \{1,2,\dots,R\}$ is normalized by the diagonal regional output matrices $\mathrm{diag}(x^r)$, $\forall\, r \in \{1,2,\dots,R\}$.

$$\begin{bmatrix} \mathbf{q}^1 \\ \vdots \\ \mathbf{q}^R \end{bmatrix} = \begin{bmatrix} \mathbf{\Psi}^{\star 11} & \cdots & \mathbf{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \mathbf{\Psi}^{\star R1} & \cdots & \mathbf{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{A}^{\star 1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{A}^{\star R} \end{bmatrix} \begin{bmatrix} \mathbf{q}^1 \\ \vdots \\ \mathbf{q}^R \end{bmatrix} + \begin{bmatrix} \mathbf{\Psi}^{\star 11} & \cdots & \mathbf{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \mathbf{\Psi}^{\star R1} & \cdots & \mathbf{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{c}^{\star 1} \\ \vdots \\ \mathbf{c}^{\star R} \end{bmatrix} \tag{13}$$

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.

2.2.3. 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[17] proposed a demand-reduction IIM that has been successfully employed to study multi-industry impacts of perturbations in supply and demand (e.g., [36]-[39]). 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.[37] 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.

2.2.4. 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. (14). 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. (15). 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. (16).

$$\hat{c}_k^r = (\hat{c}_k^r)_{\text{int}} + (\hat{c}_k^r)_G \qquad k \in \{1, \dots, K\} \tag{14}$$

$$\hat{c}_k^r - \tilde{c}_k^r = \sum_{i\in(N_+^r\cap N_k)} S_i^k \qquad k \in \{1, \dots, K\} \tag{15}$$

$$c_k^{\star r} = \frac{\sum_{i\in(N_+^r\cap N_k)} S_i^k}{\hat{x}_k^r} \qquad k \in \{1, \dots, K\} \tag{16}$$

2.2.5. Modeling Unmet Demand

As discussed by Pant et al.[37], 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, $\Delta(\hat{c}_k)_{\text{int}}$.

$$\sum_{i\in(N_{-}^{r}\cap N_k)} S_i^k = \Delta\hat{x}_k^r + \Delta(\hat{c}_k^r)_{\text{int}} \qquad k \in \{1,\dots,K\} \tag{17}$$

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. (10) with $\Delta\hat{x}_k/\hat{x}_k$. Also, a disruption in internal consumption, 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. (12) 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.[37],[40] and the transportation network vulnerability formulation of Darayi et al.[41], 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. (18). For the industries experiencing difficulties only in importing their required commodities, there exists a final consumption perturbation, as modeled in Eq. (19).

$$\frac{\Delta\hat{c}_k^r}{\hat{x}_k^r} = \frac{\sum_{i\in(N_{-}^{r}\cap N_k)} S_i^k - \Delta\hat{x}_k^r}{\hat{x}_k^r} \qquad k \in \{1,\dots,K\} \tag{18}$$

$$\mathrm{c}_k^{\star r} = \frac{\sum_{i\in(N_{-}^{r}\cap N_k)} S_i^k}{\hat{x}_k^r} - q_k^r \qquad k \in \{1,\dots,K\} \tag{19}$$

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. (16) and (19) combined with the MRIIM in Eq. (13) is implemented. While in actual situations, some industries would likely consist of both supply and demand nodes in each region, Eqs. (16) and (19) capture failure in either *only* supply nodes or *only* demand nodes within a particular industry at a region. Eq. (20) formulates the total final consumption perturbation for industry k in the case of having both exporting (supply) and importing (demand) roles.

$$\mathrm{c}_k^{\star r} = \frac{\sum_{i\in(N_{+}^{r}\cap N_k)} S_i^k}{\hat{x}_k^r} + \frac{\sum_{i\in(N_{-}^{r}\cap N_k)} S_i^k}{\hat{x}_k^r} - q_k^r \qquad k \in \{1,\dots,K\} \tag{20}$$

As a result, the perturbation vector for region r ($\mathbf{c}^{\star r}$), whose elements are captured by Eqs. (16), (19), or (20) depending on the importing/exporting role the nodes belonging to each industry in each region, parameterizes the interdependency model in Eq. (13). 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.

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. (1), a time-based formulation is proposed in Eq. (21) 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. (13), by the expected production level in monetary units, i.e. $Q_k^r = x_k^r q_k^r$. Total economic losses at each time period, Q_t,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. (21).

$$Я_t = \frac{Q_{\max} - Q_t}{Q_{\max}} \tag{21}$$

A regional restorative capacity measure is proposed in Eq. (22) that represents the economic productivity improvement in region *r* triggered by restorative decisions up to time t. Likewise, a regional-based industry-specific measure of restorative capacity at time t is formulated in Eq. (23).

$$Я_t^r = \frac{Q_{\max}^r - Q_t^r}{Q_{\max}^r} \tag{22}$$

$$Я_{k,t}^r = \frac{Q_{\mathrm{k,max}}^r - Q_{k,t}^r}{Q_{\mathrm{k,max}}^r} \tag{23}$$

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. There are multiple sets of commodities, and it is assumed that each set represents the output of a lone industry, as defined by the North American Industry Classification System (NAICS). 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
$t = 1, \dots, T$	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
$k' = 1, \dots, K'$	Index of type of commodities, where K' is the total number of commodities
$r = 1, \dots, R$	Index of regions, where R is the total number of regions
N^r	Set of nodes in the region r

Parameters	
u_{ij}	Capacity of link (i, j)
$\hat{x}_k^r$	Total production of industry k in region r in tons
$b_i^{k'}$	Mass-balance parameter representing supply/ demand/transshipment of commodity k' at node i. 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 $(K \times R) \times (K \times R)$

Variables	
$f_{ijt}^{k'}$	Integer variable representing the flow of commodity k' across link (i, j) at time t
$S_{it}^{k'}$	Integer slack variable that captures undelivered commodity k' remaining with the supplier node *i* or unsatisfied demand at demand node *i* at time *t*
μ_{ijt}	Binary variable equal to 1 when a disrupted link (i, j) recovered 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.

$$\max \sum_{t=1}^{T} Я_t \tag{24}$$

$$\sum_{k'=1}^{K'} f_{ijt}^{k\prime} \leq \beta_{ijt} u_{ij}, \qquad \forall (i,j) \in L, t = 1, \dots, T \tag{25}$$

$$\sum_{(i,j)\in L} f_{ijt}^{k'} - \sum_{(j,i)\in L} f_{jit}^{k'} + \gamma_i S_{it}^{k'} = b_i^{k'}, \qquad k' = 1, \dots, K', t = 1, \dots, T \tag{26}$$

$$\gamma_i = \begin{cases} -1 & \text{for } i \in N_- \\ +1 & \text{for } i \in N_+ \\ 0 & \text{for } i \in N_0 \end{cases} \tag{27}$$

$$\sum_{t=1}^{T} \mu_{ijt} \leq 1, \qquad \forall (i,j) \in L \tag{28}$$

$$\beta_{ijt} \leq \sum_{s=1}^{t} \mu_{ijs}, \qquad \forall (i,j) \in L, t = 1, \dots, T \tag{29}$$

$$c^{*}{}_{rt}^{k} = \frac{\sum_{k'\in\alpha^k} \sum_{i \in (N_+ \cap N^r)} S_{it}^{k'} + \sum_{k'\in\alpha^k} \sum_{i \in (N_- \cap N^r)} S_{it}^{k'}}{\hat{x}_k^r} - \omega_{kt}^r q_{kt}^r, \quad r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T \tag{30}$$

$$\frac{1}{\hat{x}_k^r} \sum_{k'\in\alpha^k} \sum_{i \in (N_- \cap N^r)} S_{it}^{k'} \leq \omega_{kt}^r \leq \hat{x}_k^r \sum_{k'\in\alpha^k} \sum_{i \in (N_- \cap N^r)} S_{it}^{k'}, r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T \tag{31}$$

$$\begin{bmatrix} \mathbf{q}_t^1 \\ \vdots \\ \mathbf{q}_t^R \end{bmatrix} = \begin{bmatrix} \mathbf{\Psi}^{\star 11} & \cdots & \mathbf{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \mathbf{\Psi}^{\star R1} & \cdots & \mathbf{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{A}^{\star 1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{A}^{\star R} \end{bmatrix} \begin{bmatrix} \mathbf{q}_t^1 \\ \vdots \\ \mathbf{q}_t^R \end{bmatrix} + \begin{bmatrix} \mathbf{\Psi}^{\star 11} & \cdots & \mathbf{\Psi}^{\star 1R} \\ \vdots & \ddots & \vdots \\ \mathbf{\Psi}^{\star R1} & \cdots & \mathbf{\Psi}^{\star RR} \end{bmatrix} \begin{bmatrix} \mathbf{c}_t^{\star 1} \\ \vdots \\ \mathbf{c}_t^{\star R} \end{bmatrix} \quad t = 1, \dots, T \tag{32}$$

$$Q_{rt}^k = x_r^k q_{rt}^k, \qquad r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T \tag{33}$$

$$\beta_{ijt} = \{0,1\}, \mu_{ijt} = \{0,1\}, \qquad \forall (i,j) \in L, t = 1, \dots, T \tag{34}$$

$$S_{it}^{k'} > 0, \qquad \forall i \in N_+, \forall j \in N_-, k' = 1, \dots, K', t = 1, \dots, T \tag{35}$$

$$c_{rt}^{\star k} > 0, q_{rt}^k > 0, Q_{rt}^k > 0, \omega_{kt}^r = \{0,1\}, \qquad r = 1, \dots, R, k = 1, \dots, K, t = 1, \dots, T \tag{36}$$

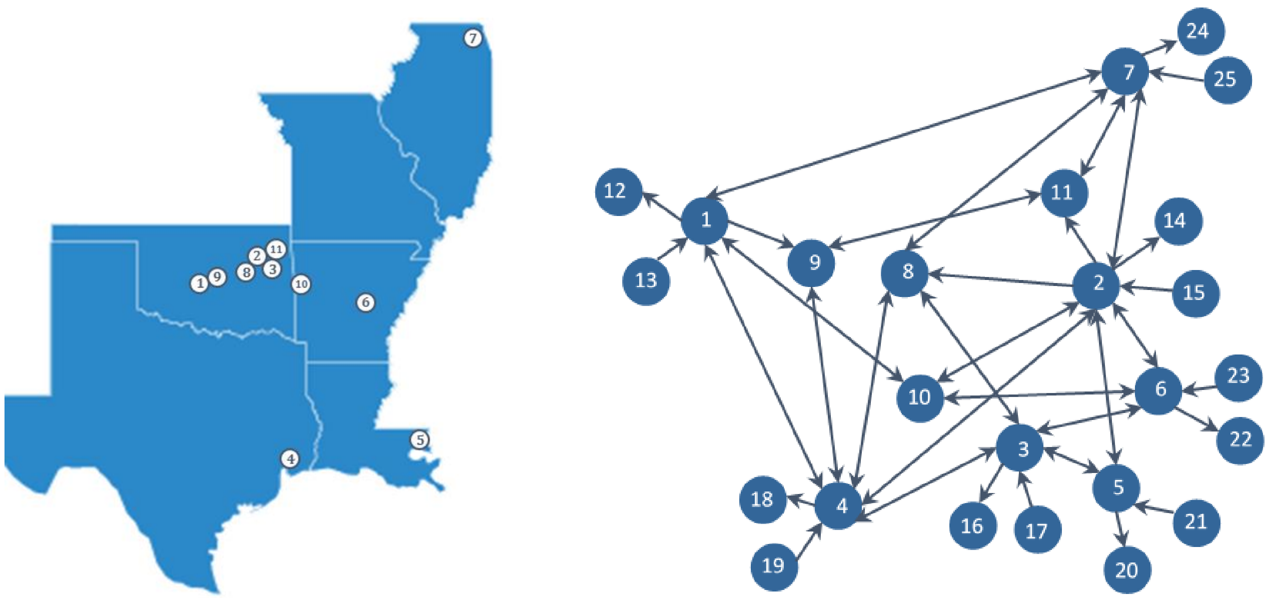
The proposed formulation optimizes the restoration efforts associated with a transportation network in the aftermath of a disruptive event. Recall that the network is presented by a directed graph $G = (N, L)$, with set of nodes N and set of links L. Due to a disruption, a set of nodes and associated links will be deactivated (β_{ijt} for disrupted links at time t_d is equal to 0). The objective function explores a restoration schedule of disrupted links that leads to the maximum proportional reduction in economic losses across the time horizon. In fact, the order of recovery for disrupted links that has been defined as μ_{ijt} is the decision should be made by a hypothetical decision maker interested in maximizing the restorative capacity of a multi-regional multi-industry economy. Eq. (26) represents the flow balance constraint for all commodities in and out of supply, demand, and transshipment nodes, in which a slack variable $S_{it}^{k\prime}$ is defined to capture undelivered commodities remaining with the suppliers, or unsatisfied demand at demand nodes. The magnitude of $S_{it}^{k\prime}$ is positive, and multiplier γ_i takes on a negative value for set of demand nodes N_-, a positive value for supply nodes N_+, and zero for transshipment nodes N_0. Note that $b_i^{k'}$ is a positive value for supply nodes, $\forall i \in N_+$, a negative value for demand nodes, $\forall i \in N_-$, and it is zero for transshipment nodes, $\forall i \in N_0$. Eqs. (28) and (29) model recovery orders. Eq. (28) shows that only one link could be recovered at a time, and when it is recovered, it remains operational for the remainder of the time horizon, as shown in Eq. (29). Eqs. (30)-(32) calculate multi-regional multi-industry inoperability caused by the remaining commodities at supply nodes and unsatisfied demand at demand nodes of different industries in different regions. And, Q_{rt}^{k}in Eq. (33) represents total economic loss of each industry, k, in each region, r ,at time, t. In Eq. (32), q_t^r is the inoperability vector, $k \times 1, \ \forall k \in K$, of all industries in region r. The proposed approach benefits from the flexibility, scalability, and efficiency of the base MCNF paradigm with respect to optimization[25], as practiced in modeling interdependencies in critical infrastructure networks (e.g., [42]).

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. Four combined business economic areas, in surrounding states, are connected to three main business economic areas within Oklahoma through a multi-modal freight transportation network. We employ the case study to implement the proposed model and evaluate and analyze the restorative efforts from different perspectives, such as, regional or industry-based economic loss caused by the disruption and network resilience behavior within restoration horizon. Three disruption scenarios are defined as the complete disruption of four different transshipment nodes. It is desired to determine the optimal schedule of network components recovery actions considering the multi-regional, multi-industry economic in the aftermath of each disruptive scenario.

Figure 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, 12, 13), the Port of Catoosa in Tulsa (node 2, 14, 15), and the Port of Muskogee (node 3, 16, 17), Texas (node 4, 18, 19), Louisiana (node 5, 20, 21), Arkansas (node 6, 22, 23), and Illinois (node 7, 24, 25)[43]. Each of the nodes could be home to either suppliers or consumers of multiple commodities, or just be an intermediate node. We do note that there are multiple sets of commodities, and it is assumed that each set belongs to a lone industry.

Table 1 briefly discusses the multi-modal freight transportation network that facilitates the flow of different commodities between the state of Oklahoma and the neighboring states. 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. 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).



(a) (b)

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

As defined by NAICS, 62 industries operate in each of the five states, therefore $\mathbf{A}^{\star}$ matrix regionalized for each state is 62×62. Due to high trade figures reported by Bureau of Transportation Statistics[32], we consider six primary industries listed in Table 1, export/import commodities from/to Oklahoma, with respect to the four considered surrounding states. Discussed previously, it is assumed that each set of commodities 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[44]-[47], a list of monthly supply and demand is presented in Table 3 (assuming constant monthly demand, or annual demand divided by 12).

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

Component	Description
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 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

Table 3. Combined monthly demands/supplies of each industry (column) at supply/demand nodes (rows) connecting through the network (in tons).

	311	324	325	327	333	339
Supply nodes						
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
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
Demand nodes						
Oklahoma City	23250	0	60000	0	17000	1100
Port of Catoosa	1064	3828	36976	635	7174	577
Port of Muskogee	285	0	21750	0	70000	0
Texas	97281	316905	204006	0	25838	30154
Louisiana	50244	18449	0	0	267	0
Arkansas	265245	153518	381180	41038	156	54494
Illinois	0	0	0	199304	0	64039

3.1. STEP 1 APPLIED: 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[48]. The monthly capacity of each link is estimated from historical data as a shared constraint for all commodities flowing on the link[49], 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 removal of multiple network components, (i.e., nodes and associated links) at time t_d (when disruption happens). 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]). Recovery actions will be taken throughout the time horizon and it is possible to recover one and only one link at a time. Three disruption scenarios are defined as the removal of multiple intermediate nodes and associated links within the network. In the first scenario, it is assumed that the disruptive event would deactivate nodes 10, 9, 11 and all their associated links, together with three links that connect node 7 to nodes 1, 2, and 8. The second disruption scenario considers the loss of all associated links of nodes 8, 9, 11 and two links that connect node 4 to node 1 and 3. The third scenario disables nodes 10, 8, 11 and all the associated links. The disruptive event causes a failure within the supply-demand network. Failure in the form remaining commodities with suppliers or/and unsatisfied demands at demand nodes, as represented by $S_{it}^{k'}$, affects industry output and result in propagated inoperability through many of the interconnected industries located in multiple regions.

In the illustrative example, three supply/demand nodes are within the state of Oklahoma and four supply/demand nodes are located in Texas, Louisiana, Arkansas, and Illinois. Tables 4 and 5 report the sum of the slack (remaining supply) by sets of commodities belonging to a particular industry at supply nodes, $\sum_{k' \in \alpha^k} \sum_{i \in (N_+ \cap N^r)} S_{it}^{k'}$, in a particular region (state) following a desruption scenario, and $\sum_{k' \in \alpha^k} \sum_{i \in (N_- \cap N^r)} S_{it}^{k'}$, the sum of the slack (unsatisfied demand) by sets of commodities belonging to a particular industry at demand nodes in a partiular region (state), respectively, omitting the flow on the disrupted components from the baseline flow within the network. As shown in Tables 4 and 5, most industry sectors in these five states are vulnerable in all disruption scenarios whether the failure occures in the form of reminingn commodities at suppliers or unmet demand at demand nodes.

3.2. STEP 2 APPLIED: MULTI-INDUSTRY IMPACT

When a disruption happens, supply-demand network failure in the form of remining commodities at suppliers and unmet demands at demand nodes causes economic inoperability in multiple industry sectors located in multiple regions. The propagation of economic inoperability in a network of interconnected multi-regional industry sectors is captured by q_r^k in vector q^R for each region in Eq. (10), representing the extent to which an industry output will not be produced or an industry input will not be received. And, the effect of the disruption on the economy of each region (state) is captured by Q^r.

Following a disruption, the remaining commodities at suppliers and unmet demands at demand nodes shown in Tables 4 and 5, respectively, cause economic inoperability perturbated throughout the multi-regional, multi-industry network, calculated with Eq. (32). This inoperability is translated into a monetary value to represent the economic loss of industry *k* in region *r*, in Eq. (33). In Tables 6 through 9, it is shown how different disruption scenarios affect industry sectors in multiple states, assuming that no recovery action taken, and just following a disruption it is tried to facilitate the commodity flows throughout the disrupted network using its maximum capacity. The *Machinery* industry (333) is the most vulnerable sector in the case of each three disruptive scenarios. Each of these disruption scenarios also affects the operability of the *Miscellaneous manufacturing* industry (339), yet in lesser extent than industry (333). It is also clear that almost all the six industry sectors in all of these five states would be affected in either of these three disruption scenarios (e.g. economic loss caused by the first disruption scenario is graphically depicted in Figure 5).

Table 4. Tons of remaining commodities (by industry) at suppliers with the removal of network components.

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

Table 5. Tons of unsatisfied commodities (by industry) at demand nodes with the removal of network components.

Scenario	Region	311	324	325	327	333	339
1	Oklahoma	24599	3828	118726	635	94174	1677
1	Texas	97281	316906	204006	0	25838	30154
1	Louisiana	50244	18450	0	0	267	0
1	Arkansas	265245	153518	381180	41038	156	54494
1	Illinois	0	0	0	199304	0	0
2	Oklahoma	24599	3828	118726	635	94174	1677
2	Texas	97281	316906	204006	0	25838	30154
2	Louisiana	50244	18450	0	0	267	0
2	Arkansas	265245	153518	381180	41038	156	54494
2	Illinois	0	0	0	199304	0	64039
3	Oklahoma	24599	3828	118726	635	24174	1677
3	Texas	97281	316906	204006	0	25838	30154
3	Louisiana	50244	18450	0	0	267	0
3	Arkansas	265245	119556	381180	9152	0	24473
3	Illinois	0	0	0	199304	0	0

Tables 6 through 9 represent 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 total economic loss in each state, and (iii) a detailed report of the total economic loss in each of the six industry sectors under study.

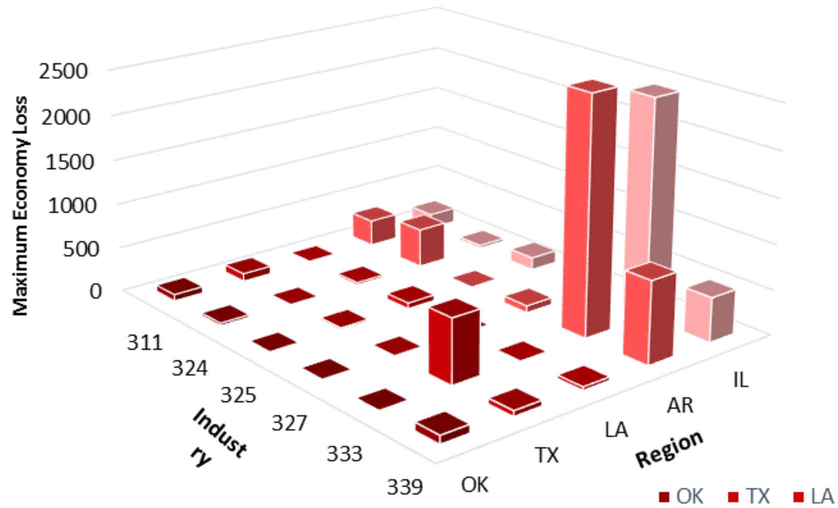


Figure 5. Maximum economic loss associated with each industry in each region.

Table 6. Maximum total economic loss across all industries and regions for each disruption scenario.

Scenario 1	Scenario 2	Scenario 3
14707.40	12711.9	13340.7

Table 7. Maximum economic loss for each region for each disruption scenario.

Region	Scenario 1	Scenario 2	Scenario 3
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

Table 8. Maximum economic loss for each industry for each disruption scenario.

Industry	Scenario 1	Scenario 2	Scenario 3
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

Table 9. Maximum economic loss for each industry by each region for each disruption scenario.

Region	Industry	Scenario 1	Scenario 2	Scenario 3
Oklahoma	311	78.57	71.08	46.33
Oklahoma	324	27.39	27.30	0.55
Oklahoma	325	4.43	3.95	3.06
Oklahoma	327	14.25	13.04	7.35
Oklahoma	333	5.23	6.98	0.00
Oklahoma	339	105.65	90.02	94.58
Texas	311	81.14	86.91	74.25
Texas	324	0.07	0.15	0.06
Texas	325	18.59	19.45	16.99
Texas	327	4.79	8.00	4.38
Texas	333	732.12	712.86	663.06
Texas	339	61.06	59.30	55.57
Louisiana	311	13.46	13.03	3.44
Louisiana	324	25.47	24.13	6.70
Louisiana	325	72.26	63.32	61.53
Louisiana	327	3.86	3.81	0.64
Louisiana	333	0.00	0.00	0.00
Louisiana	339	42.55	36.63	36.35
Arkansas	311	349.04	293.91	329.30
Arkansas	324	516.65	434.64	489.19
Arkansas	325	20.14	17.03	18.97
Arkansas	327	91.17	76.81	85.95
Arkansas	333	3113.43	2626.63	2939.40
Arkansas	339	1085.99	913.65	1029.39
Illinois	311	194.04	168.08	177.76
Illinois	324	36.38	32.75	33.96
Illinois	325	161.05	139.44	143.76
Illinois	327	34.63	30.54	30.90
Illinois	333	2809.18	2415.48	2463.21
Illinois	339	580.93	495.07	529.63

3.3. STEP 3 APPLIED: PLANNING FOR RESTORATIVE CAPACITY

We applied the proposed freight transportation network recovery methodology to enhance restorative capacity of the network following a disruption in three different disruption scenarios and run our computational experiment on an Intel Core™ i7-7500U CPU 2.90GHz (with 32 GB RAM) using Gurobi 7.0.2 on Python 2.7.13. As it is discussed in Section 2.3, the proposed model is supposed to enhance restorative capacity in a network of interconnected industries located in multiple regions by devising an order of recovery by which total economic loss can be avoided will be maximized ($\max \sum_{t=1}^{T} Я_t$). As graphically depicted in Figure 6, the goal is to enhance system resilience via devising an order of recovery actions that improves restorative capacity of the network. The proportional value of the maximum loss that can be avoided by recovery decisions has been considered as the system performance, a measure to monitor the trajectory of the economic productivity in the whole system. When a disruption happens (t_d=1), network failure causes the economic loss in a network of interconnected industries from multiple regions and degrades economic productivity. In scenarios 1 and 2, system performance is fully recovered when al 12 disrupted links are repaired while in scenario 3, network functionality is recovered at time 7, after repairing 7 components. This shows the importance of links 4-1, 4-3, 7-1, 7-2, and 7-8 that are functional in scenario 3 but some are disrupted in either of scenarios 1 and 2. It is worth mentioning that the order of recovery actions is devised to enhance the restorative capacity in the whole system which consists of five interconnected states.

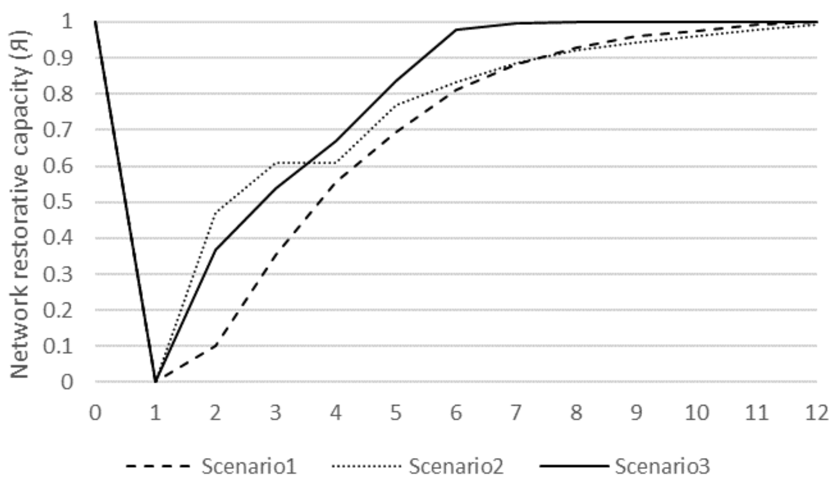
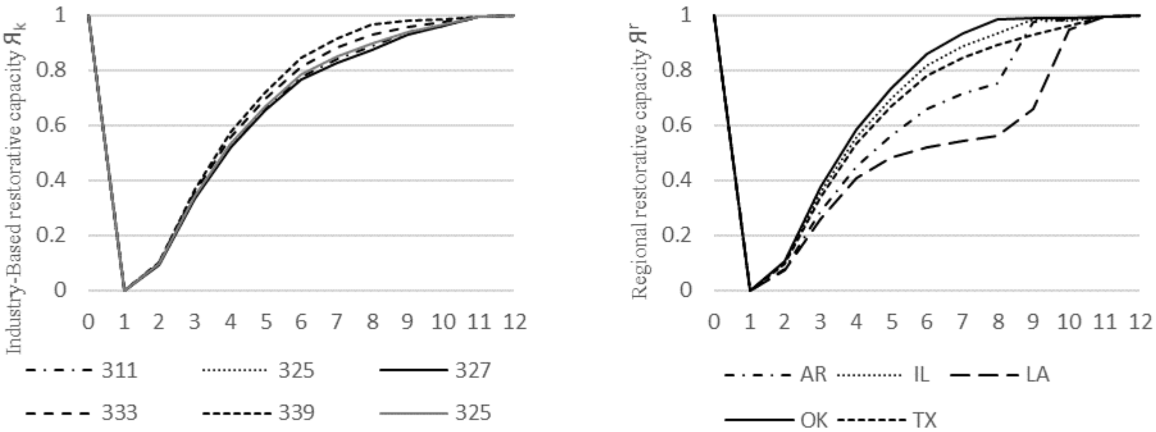


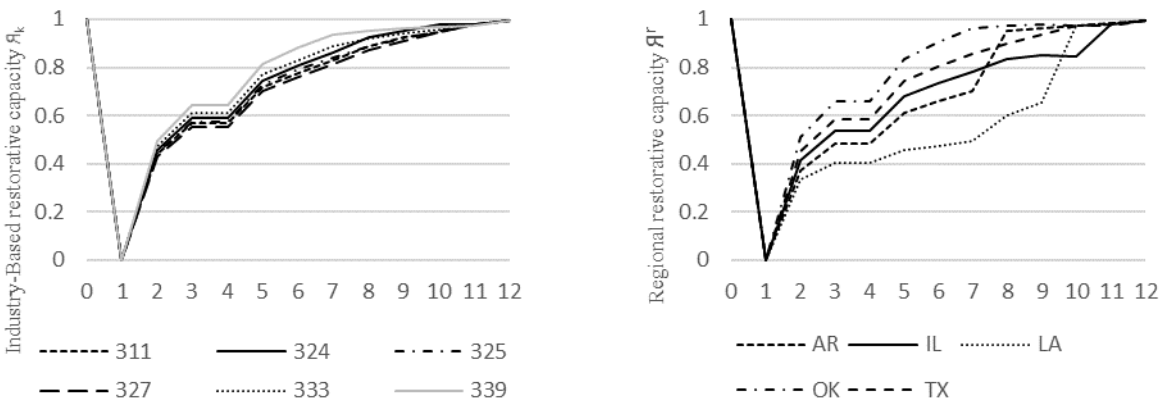
Figure 6. Total system economic resilience trajectory via recovery actions.

In Figures 7-9, the trajectory of economic productivity via the order of recovery devised in each disruption scenario (considering the total economic resilience in the entire network) is monitored for all six industries and all five regions (states). Figures 10-12 illustrated the regional-based, industry-specific inoperability trajectories via recovery actions that monitor the proportional extent to which inoperability is improved for different industries located in different regions. Though a consistent industry-based/regional system recovery is depicted in Figures 7-9 for all six industry sectors and all five states, Figures 10-12 show that the multi-regional, multi-industry perspective in devising recovery actions might not be of benefit to all regions/industries. In fact, the effect of a recovery action at time t in maximizing the *total economic loss that can be avoided* is more important than region/industry specific impacts of the recovery action. In scenarios 1 and 2, the two lowest system recovery ratios happen in Louisiana and Arkansas. This caused by the structure of the network and the dependency of these two states on particular network components (i.e. associated links to node 4 and 7) that necessitates the recovery of almost all disrupted components for full economic productivity of these two regions. Also, Texas, Illinois, and Oklahoma have the highest recovery ratio enforced by their share in the total economy and, of course, higher connectivity in the network. As shown in Figures 7a and 8a, high-dollar industries like *Petroleum and coal products* (324) do not necessarily have the highest recovery ratios, and the share of each industry sector to the entire economy and the topological connectivity of suppliers and consumers of commodities belonging to that industry prioritize recovery actions.



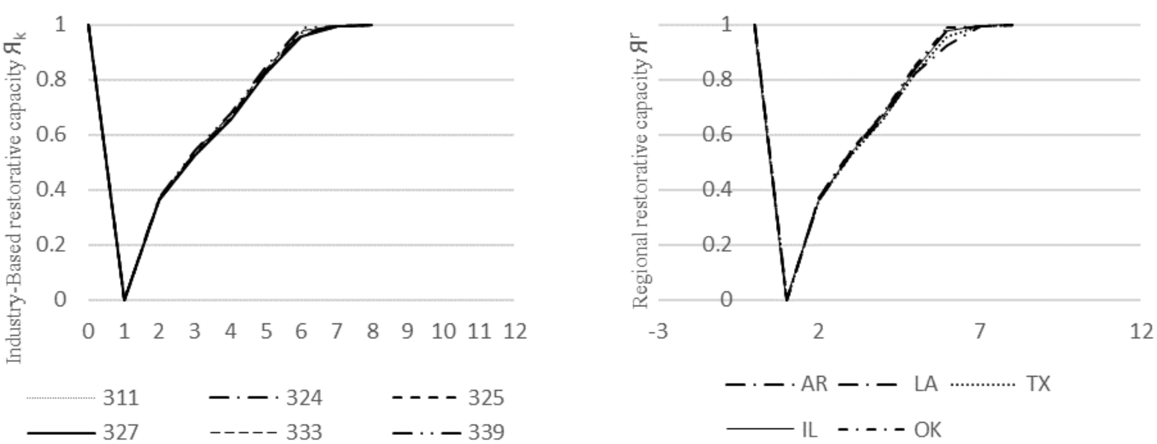
(a) (b)

Figure 7. Economic resilience trajectory (a) for each industry and (b) in each region for Scenario 1.



(a) (b)

Figure 8. Economic resilience trajectory (a) for each industry and (b) in each region for Scenario 2.



(a) (b)

Figure 9. Economic resilience trajectory (a) for each industry and (b) in each region for Scenario 3.

As shown in Figures 10-12, regional-based, industry-specific inoperability trajectories via recovery actions varies for different industry sectors in different regions. Monitoring the trajectory of economic inoperability, as 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, shows how the recovery actions affect each of the six industry sectors in all five states. As shown in Figure 12d, the higher the share of an industry sector in the economy of a region is (e.g., *Machinery* (333) in Oklahoma), the more vulnerable it is to disruption scenarios which deactivate highly connected components associated to the suppliers/consumers in that region (e.g., nodes 8, 9, 11). Though the magnitude of economic inoperability imposed on different industries in the same region by a disruption might vary (Figures 10-12)Figure 10 in highly connected regions with more share in the whole economy (Texas, Oklahoma, Illinois), the recovery trajectory has almost the same slope for most industries in that particular region. Also, in Figure 11, a consistent recovery slope is shown for multiple industries located in the same region that is different from variable recovery rations shown in Figures 10a,c and 11a,c, and points out the importance of the network connectivity in addition to the share of the region in the entire economy.

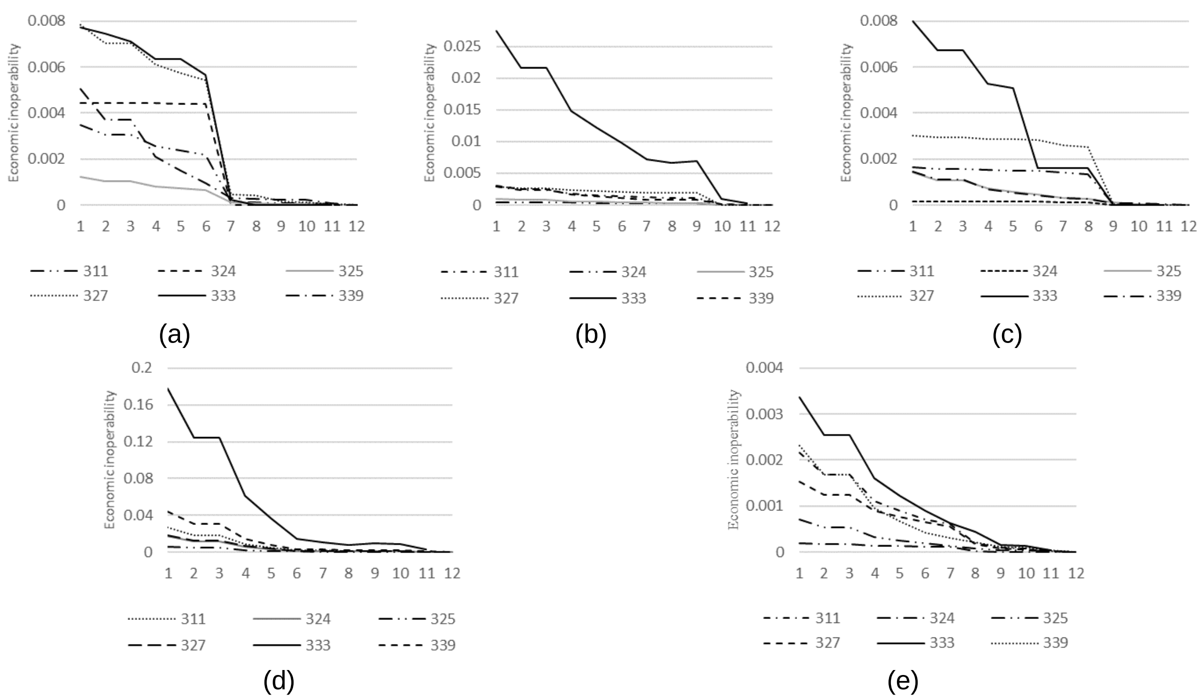


Figure 10. Regional-based, industry-specific system recovery trajectory: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, and (e) Texas for Scenario 1.

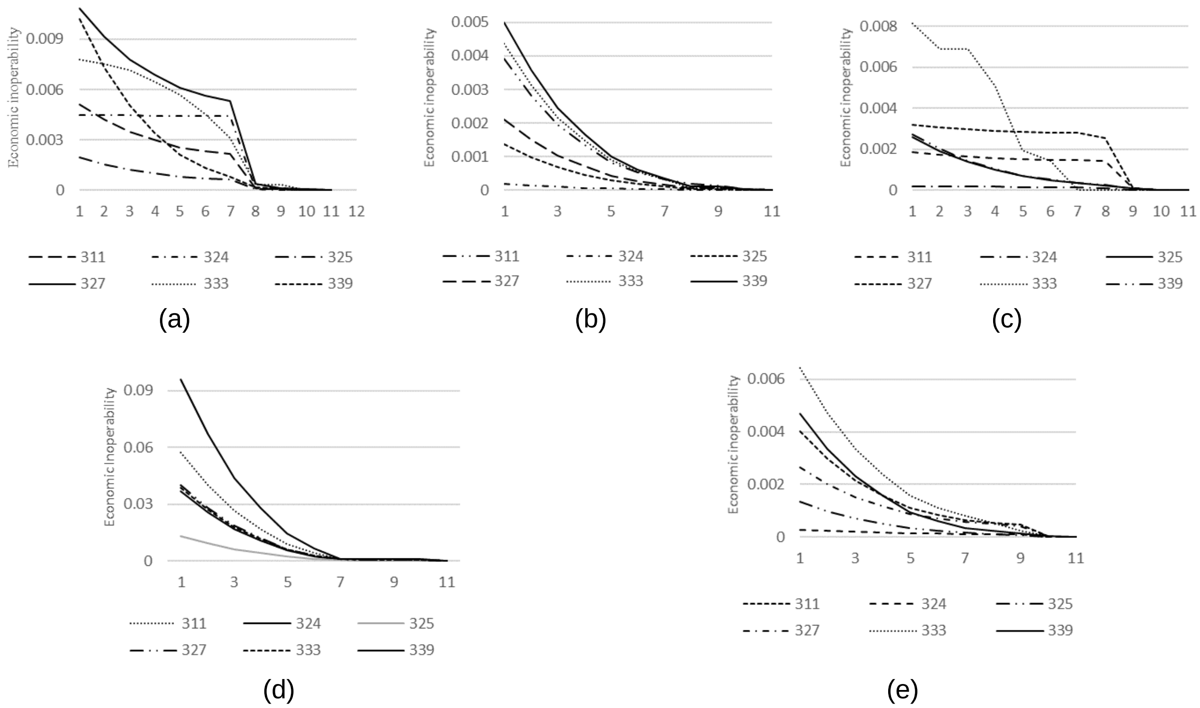


Figure 11. Regional-based, industry-specific system recovery trajectory: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, and (e) Texas for Scenario 2.

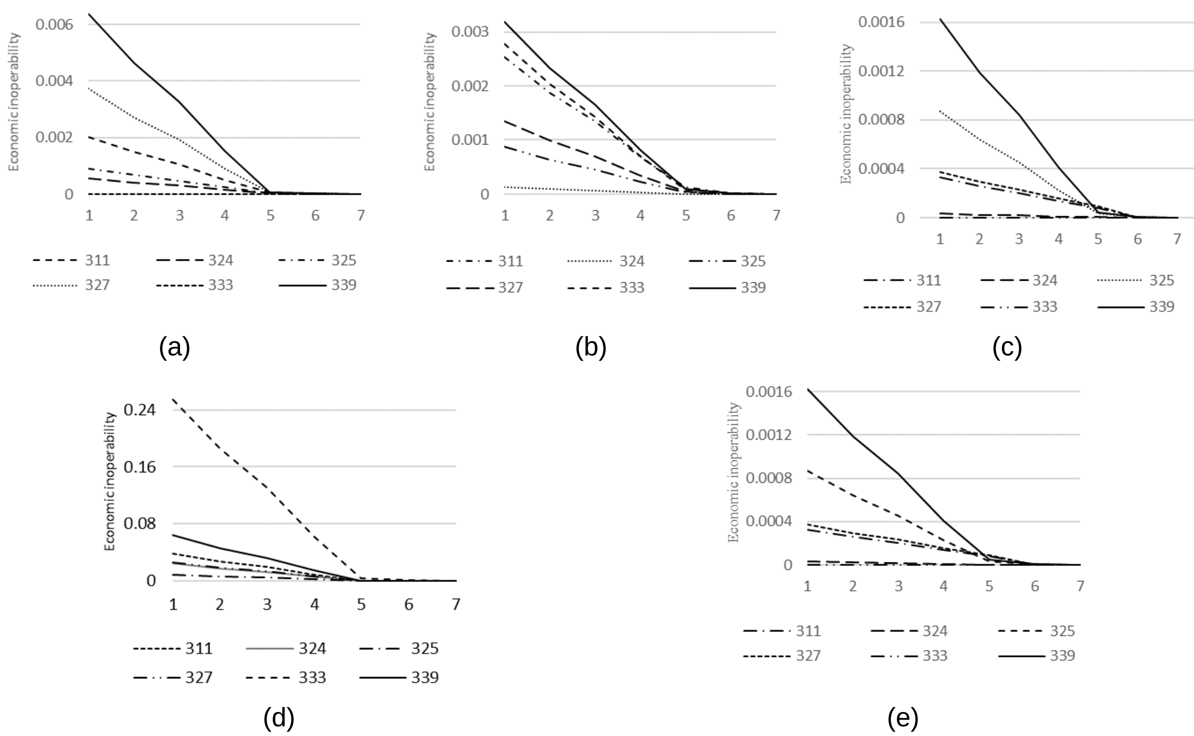


Figure 12. Regional-based, industry-specific system recovery trajectory: (a) Arkansas, (b) Illinois, (c) Louisiana, (d) Oklahoma, and (e) Texas for Scenario 3.

4. CONCLUSIONS

The focus of this work is to enhance network resilience via restorative capacity. 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 a multi-regional economic interdependency model. And, a measure of restorative capacity, as the extent to which a freight transportation network is capable of being recovered through the assignment of work crews, is proposed to analyze a broader perspective on freight transportation network considering its role in the economic productivity. In fact, the goal is to maximize the economic loss that can be avoided by recovery decisions.

The primary contribution of this approach is the integration of the multi-commodity network flow representation of the multi-modal transportation network with a multi-regional, multi-industry economic inoperability model to propose a framework to enhance infrastructure network resilience through recovery decisions. A stylized case study of a multi-modal transportation network that connects state of Oklahoma to surrounding states is considered to illustrate the developed recovery analysis paradigm.

Regional and industry-specific economic impacts of recovery decisions are analyzed. It is shown that recovery actions are devised to maximize *total economic loss that can be avoided* rather than considering region/industry specific impacts of the recoveries. In general, 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.

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. The model can be further improved by considering proportional recovery and scheduling crews to recover multiple disrupted components at a time.

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