Investing in Absorptive Capacity in Interdependent Infrastructure and Industry Sectors

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Abstract: Freight transportation infrastructure systems facilitate commodity flows across multiple industries. The closure of key infrastructures leads to an interruption of economic productivity that propagates through a system of interconnected industries. Investing in infrastructure and key industries can reduce the vulnerability of many industries by improving their ability to maintain functionality when shocked. This work investigates how a limited budget could be allocated to multiple industries to fortify them prior to a disruption to ultimately enhance the economic resilience across all industries by reducing the vulnerability of the underlying infrastructure. A risk-based economic interdependency model is used to implement a new measure of absorptive capacity to examine the propagation of a failure throughout the economy given the fortification of industry sectors. Sources of uncertainty in this data-driven model are considered, and a soft-robust optimization model is proposed to devise budget allocation under uncertainty. The approach is illustrated with an inland waterway port case study. The results can provide decision makers with managerial insights about how the economic interdependency affects the industries' share of a budget to enhance absorptive capacity and how the level of budget affects the decision-making process for allocating resources. **DOI: 10.1061/(ASCE)IS.1943-555X.0000514.**

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Introduction

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

Several definitions of *resilience* have been proposed, including the ability to withstand, adapt to, and recover from a disruption. A definition with which many would largely agree (The White House 2011). Vugrin and Camphouse (2011) defines the *resilience capacity* of a system as a function of the following: (1) *absorptive capacity*, or the extent to which a system is able to absorb shocks from disruptive events, (2) *adaptive capacity*, or the extent to which a system can quickly adapt after a disruption by temporary means, and (3) *restorative capacity*, or the extent to which the system can recover from a disruption or be reconstructed in the long term. Barker et al. (2013) highlights that the collection of absorptive and adaptive capacities addresses vulnerability mitigation, or to what extent an infrastructure withstands a disruptive event. The restorative capacity is analogous to recoverability, or the ability of the infrastructure to recover to a desired level of performance in a timely manner. The capacities contributing to resilience, as well as the dimensions of vulnerability and recoverability, are characteristics exhibited by resilient systems and could be measured in a number of context-specific ways.

As such, absorptive, adaptive, and restorative capacities can be viewed as first, second, and third lines of defense, respectively (Hosseini and Barker 2015, Hosseini et al. 2016). Fig. 1 highlights the temporal relationship among absorptive, adaptive, and restorative capacities. In this figure, we measure system performance in each time period with $\varphi(t)$ (e.g., customers with power, travel time in a transportation network, and total flow reaching to demand

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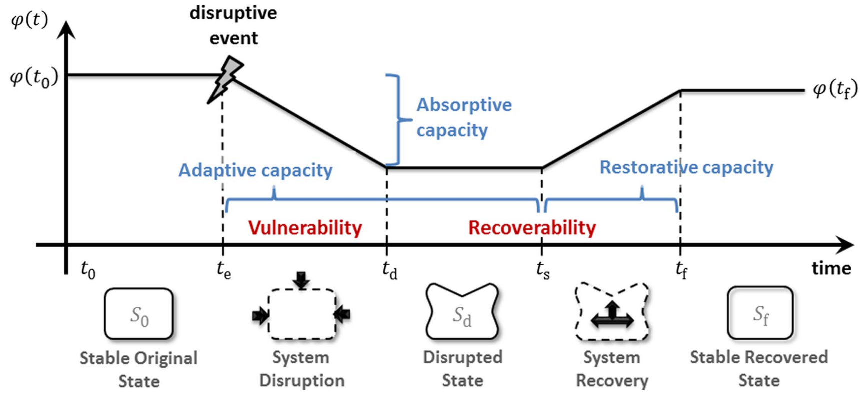

Fig. 1. Relationship between the vulnerability and recoverability dimensions of resilience and the components of absorptive capacity with respect to system performance $\varphi(t)$.

nodes). In an example of improving absorptive capacity, Bienstock and Mattia (2007) developed an optimization model to increase powerline capacities to prevent large scale cascading blackouts in a power network. An example of adaptive capacity included robust strategies to respond to the dramatic climate change in water management systems in which simulation models of several disruption scenarios assess options to ameliorate vulnerabilities in the short term (Lempert and Groves 2010). Finally, debris removal from a transportation network after a natural disaster was an example of restorative capacity (Çelik et al. 2015).

This paper focuses on reducing vulnerability via absorptive capacity. The idea of absorptive capacity has also been referred to as *static resilience*, or "the ability of the system to maintain functionality when shocked" (Rose 2007). However, this term has evolved into absorptive capacity integrating into the newly defined concept of resilience (Vugrin and Camphouse 2011). Mathematically, static resilience is measured in terms of the difference between the maximum potential drop in system performance and the estimated performance drop (Rose 2004). That is, no notion of recovery is considered, only the ability to withstand the initial disruption. This is depicted graphically in Fig. 2 and mathematically in Eq. (1), where $\%\Delta\mathrm{DY}$ and $\%\Delta\mathrm{DY}^{\max}$ are calculated with $100\% \times [\varphi(t_e) - \varphi'(t_d)]/\varphi(t_e)$, and $\%\Delta\mathrm{DY}$ = actual percentage change in the performance of the system following a disruptive event when a number of limited resources are allocated in proactively to fortify industry sectors before disruptions; $\%\Delta\mathrm{DY}^{\max}$ = maximum percentage change given the worst-case level of performance (Rose 2009). This quantitative approach is used in this study to define a performance measure for the system's ability to absorb shocks ($\%\Delta\mathrm{DY}^{\max} - \%\Delta\mathrm{DY}$) from disruptive events, though we prefer the term *absorptive capacity* rather than static resilience.

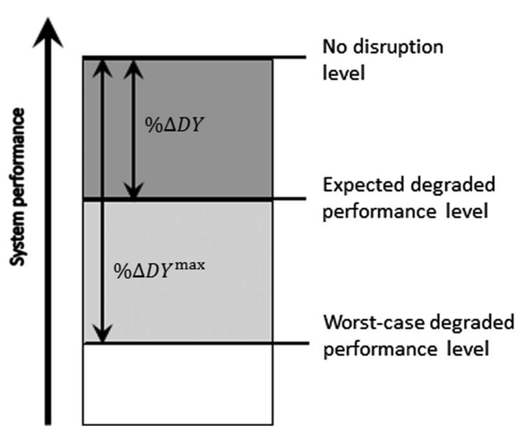

Fig. 2. Performance components of static resilience. (Reprinted from *Reliability Engineering & System Safety*, Vol. 125, R. Pant, K. Barker, and C. W. Zobel, "Static and dynamic metrics or economic resilience for interdepended infrastructure and industry sectors," pp. 92–102, © 2014, with permission from Elsevier.)

While Fig. 2, from Pant et al. (2014), represents changes in system performance in a general sense, Rose (2009) provides a more specific application, where $\%\Delta\mathrm{DY}$ and $\%\Delta\mathrm{DY}^{\max}$ refer to changes in total performance, after infrastructure fortification, and in a worst-case situation, respectively, in a set of interconnected industries. In this sense, these measures are analogous to the concept of inoperability, a well-studied topic in the literature of interdependent industries and infrastructures (Santos and Haimes 2004; Barker and Haimes 2009; Barker and Santos 2010a, b). Inoperability (q) quantifies the proportional extent to which a system does not function in an as-planned manner. That is, where other measures quantify system performance in application-specific terms (e.g., flow capacity, connectivity, production output), inoperability provides a more general proportional metric of performance relative to an as-planned value. As such, we adopt $\%\Delta\mathrm{DY} = q$; $\%\Delta\mathrm{DY}^{\max} = q_{\max}$ in this work, and we relate absorptive capacity to these inoperability measures

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

This paper seeks to answer: how should limited resources are allocated to harden individual industries effectively to enhance absorptive capacity with total economic impacts in mind? These economic impacts are realized due to freight disruptions. Freight transportation infrastructure disruptions lead not only to physical damage but also to an interruption of economic productivity across multiple industries due to infrastructure inoperability (Ham et al. 2005; Park et al. 2011). Arnold et al. (2006) analyzed the economic impacts of disruptions in container traffic in the ports of Los Angeles and Long Beach, California. Pant et al. (2011), using the inoperability input-output model (IIM), and (Santos and Haimes 2004) showed how a local disruption in the Port of Catoosa in Tulsa, Oklahoma, would affect multiple industries within the state and neighboring states that trade with Oklahoma. IIM is a data-driven interdependent disruption evaluation model that has been widely used to analyze interdependent connections among industry sectors (Pant et al. 2014). The model proposed a balance supply-demand equilibrium for interacting industries. Understanding the absorptive capacities of affected industries could assist in preparedness planning against disruptions. In particular, preparedness plans could enhance the ability of the industries to absorb shocks from the disruptive events and lessen the maximum economic inoperability that the series of interdependent industries would experience.

This paper establishes inoperability through the IIM as a means to measure absorptive capacity in interdependent industries. This research addresses (1) defining a measure of absorptive capacity to invest for resilience in an interdependent economic system; and (2) planning for absorptive capacity under uncertainty; while (3) addressing some of the uncertainties of the model.

Methodological Background

The IIM is an extension of the economic input-output model (Leontief 1986). The input-output model has been widely used in analyzing the interdependent connections among industries (Santos and Haimes 2004).

In a system of n interacting industries under a static equilibrium, the total output of the ith industry is distributed to all other industries and satisfies external demand. This equilibrium condition is described with $x_i = \sum_{j=1}^{n} z_{ij} + c_i$, where x_i = output; c_i = external demand for industry i; and z_{ij} describes the flow of commodities output from industry i and is used as input to production in industry j. The flow of commodities z_{ij} is assumed to be proportional to the output of industry j, expressed as $z_{ij} = a_{ij}x_j$. The common form of the Leontief input-output model is expressed in Eq. (2), where $\mathbf{x}$ is an $n \times 1$ vector of industry production outputs, $\mathbf{A}$ is an $n \times n$ industry-by-industry matrix of interdependency coefficients, and $\mathbf{c}$ is a $n \times 1$ vector of final demands. The model shows that total production is made up to satisfy industry-to-industry intermediate production ($\mathbf{Ax}$) and final demands ($\mathbf{c}$)

$$\mathbf{x} = \mathbf{Ax} + \mathbf{c} \Rightarrow \mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{c} \tag{2}$$

Instead of describing the connections between the interdependent industries in terms of commodity flow in monetary units (e.g., dollars), the IIM illustrates how normalized production losses propagate through all interconnected industries. The IIM is provided in Eq. (3) (Santos and Haimes 2004), which describes the relationships among n infrastructure and industry sectors, resulting in matrices of size $n \times n$ and vectors of length n

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

Vector $\mathbf{q}$ here is a vector of infrastructure and industry inoperabilities describing the extent to which ideal functionality is not realized following a disruptive event. Inoperability for sector i is defined in Eq. (4), where the as-planned total output is represented with $\hat{x}_i$ and degraded total output resulting from a disruption is represented with $\tilde{x}_i$. An inoperability of 0 suggests that an industry is operating at normal production levels, while an inoperability of 1 means that the industry is not producing at all

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

Normalized interdependency matrix $\mathbf{A}^{\star}$ is a modified version of the original $\mathbf{A}$ matrix describing the extent of economic interdependence among a set of infrastructure and industry sectors. Shown in Eq. (5), the row elements of $\mathbf{A}^{\star}$ indicate the proportions of additional inoperability that are contributed by a column sector to the row sector

$$a^{\star}_{ij} = a_{ij}(\hat{x}_j/\hat{x}_i) \Leftrightarrow \mathbf{A}^{\star} = [\mathrm{diag}(\hat{\mathbf{x}})]^{-1}\mathbf{A}[\mathrm{diag}(\hat{\mathbf{x}})] \tag{5}$$

Eq. (6) provides the calculation of $\mathbf{c}^{\star}$, a vector of normalized demand reduction. The elements of $\mathbf{c}^{\star}$ represent the difference in as-planned demand $\hat{c}_i$ and perturbed demand $\tilde{c}_i$ divided by as-planned production, quantifying the reduced final demand for sector i as a proportion of total as-planned output

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

As is evident from Eq. (3), the IIM, like the economic input-output model of Eq. (2), is a demand-driven model. Specifically, in the IIM, disruptions are translated to demand perturbations giving direct economic losses, following which the indirect economic losses can be estimated through Eq. (3). An example of a demand perturbation, as discussed subsequently in the case study, would include unsatisfied demand in the petroleum and coal products industry resulting from a closure of an inland waterway port.

Total economic losses, the combination of direct and indirect losses, can be calculated by multiplying each industry's production level by its inoperability level: for industry i, $Q_i = x_i q_i$, or for the entire economy of industries, $Q = \mathbf{x}^T\mathbf{q}$. As such, planning decisions can be made with respect to inoperability or economic impact at the sector level or with respect to economic impact at the multisector level.

Criticisms of the basic IIM include its linear nature and its treatment of interactions of industries as constant after a disruption (Kujawski 2006). However, the linear nature of the model enables it to be easily used in an optimization formulation (e.g., relative to a nonlinear computable general equilibrium model to describe the interactions among industries) as is proposed in this paper. And the constant nature of the parameters of the model is assumed here due to the short-term nature of the analysis, as changes in the economy over time (e.g., substitution among industries) do not affect the proposed formulation. Further, while data describing the parameters of the IIM are published annually by the US Bureau of Economic Analysis (BEA) and many other countries worldwide, an obvious benefit of the IIM enterprise, we instead propose a robust formulation to account for any uncertainty that may be present in these parameters. Our proposed formulation also accounts for disruptions driven by unsatisfied demand at demand nodes and residual supply at supply nodes both of which can be represented with the IIM, which is demand-driven in nature.

Absorptive Capacity Measures

As discussed previously, the interdependent impacts of a disruption are calculated using the IIM, and subsequently, a measure of absorptive capacity is defined based on the concept of static economic resilience (Rose 2009; Pant et al. 2014). We propose an optimization model to devise a strategy to allocate limited budget to industries to enhance absorptive capacity. Epistemic data uncertainty in the IIM is considered, and as such, decision-making under uncertainty is discussed.

Defining Absorptive Capacity with Inoperability

As suggested previously, the percentage change in the performance of a system (%ΔDY) is analogous to the measure of inoperability (q), which represents the proportional extent to which a system is not properly functioning. If we define $q_{\max}$ as the maximum possible inoperability that could be experienced after a disruptive event, a measure of absorptive capacity is provided in Eq. (7). Absorptive capacity of sector i is referenced with convention $Я^S_i$, adopting the Я notation of Whitson and Ramirez-Marquez (2009) because R often refers to reliability

$$Я_i^S = \frac{\%\Delta\mathrm{DY}^{\max} - \%\Delta\mathrm{DY}}{\%\Delta\mathrm{DY}^{\max}} = \frac{q_{i,\max} - q_i}{q_{i,\max}} \tag{7}$$

Using the convention $\mathbf{D}^\star = [d_{ij}^\star] = [\mathbf{I} - \mathbf{A}^\star]^{-1}$, Eq. (3) can be written as $\mathbf{q} = \mathbf{D}^\star \mathbf{c}^\star$. As such, inoperability in sector i can be represented with Eq. (8)

$$q_i = \sum_{j=1}^{n} d_{ij}^\star c_j^\star \tag{8}$$

As shown in Eq. (9), using the demand-driven paradigm, the absorptive capacity for sector i can be written as a function of maximum and expected demand perturbation levels, $c_{j,\max}^\star$ and $c_j^\star$, respectively. The proportional "savings" in inoperability is measured by $Я_i^S$ when a priori planning can stave off the worst-case inoperability outcome in favor of reduced inoperability

$$Я_i^S = \frac{\sum_{j=1}^n d_{ij}^\star c_{j,\max}^\star - \sum_{j=1}^n d_{ij}^\star c_j^\star}{\sum_{j=1}^n d_{ij}^\star c_{j,\max}^\star} = \frac{\sum_{j=1}^n d_{ij}^\star (c_{j,\max}^\star - c_j^\star)}{\sum_{j=1}^n d_{ij}^\star c_{j,\max}^\star} \tag{9}$$

To capture absorptive capacity across the entire set of interdependent infrastructures and industry sectors, a more appropriate economic resilience metric would account for the widespread ability of sectors to collectively maintain operability following a disruptive event. As such, individual sector inoperability is multiplied by sector output in dollar terms. In summation form, this is represented with $Q_i = \sum_{j=1}^n x_i d_{ij}^\star c_j^\star$. The resulting absorptive capacity metric is provided in Eq. (10)

$$\begin{aligned} Я_{\text{total}}^S &= \frac{\sum_{i=1}^n \sum_{j=1}^n x_i d_{ij}^\star c_{j,\max}^\star - \sum_{i=1}^n \sum_{j=1}^n x_i d_{ij}^\star c_j^\star}{\sum_{i=1}^n \sum_{j=1}^n x_i d_{ij}^\star c_{j,\max}^\star} \\ &= \frac{\sum_{i=1}^n \sum_{j=1}^n x_i d_{ij}^\star (c_{j,\max}^\star - c_j^\star)}{\sum_{i=1}^n \sum_{j=1}^n x_i d_{ij}^\star c_{j,\max}^\star} \end{aligned} \tag{10}$$

Planning for Absorptive Capacity

Resource allocation requires developing strategies that reduce demand perturbations effectively, leading to economic resilience. This demand-driven model is consistent with the idea that absorptive capacity (i.e., to what extent the system can withstand the disruptions), along with investments on expanding the redundancy in infrastructure networks, is the efficient utilization of resources and not system repair (Rose 2007).

Assume that a disruptive event perturbs demand [perhaps directly, or perhaps as a forced demand reduction because of a supply shortage (Darayi et al. 2017)] in $m \le n$ sectors. The worst-case demand perturbations in each of these m sectors are given by $c_{l,\max}^\star$, $l = \{1, \ldots, m\}$. The implementation of preparedness, or resilience-building, activities is concerned with reducing $c_{l,\max}^\star$ through efficient resource allocation. If r_l is a preparedness strategy adopted to reduce the initial sector l demand perturbation impact, the effectiveness of r_l is measured in terms of the new resulting demand perturbation in Eq. (11). All sector demand perturbations are governed by Eq. (12)

$$c_l^\star = f_l(c_{l,\max}^\star, r_l) \tag{11}$$

$$c_i^\star = \begin{cases} c_l^\star & \text{if } i \in l \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

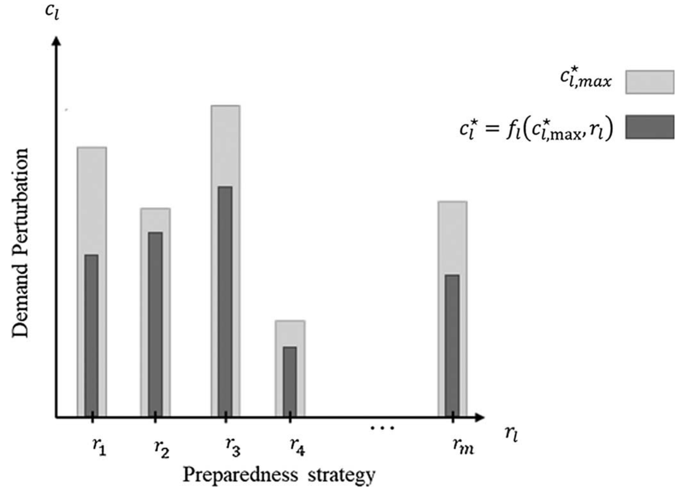

Fig. 3. Candidate functional relationships between $c_l^\star$ and r_l.

Assuming a numerically higher value for r_l results in a more effective preparedness strategy, some candidate graphical relationships between $c_l^\star$ and r_l are conceptually depicted in Fig. 3 with the upper bound being $c_{l,\max}^\star$.

Since implementing preparedness strategies comes at a cost, there is a finite budget that governs the maximum possible values taken by r_l. If $g_l(r_l)$ expresses the cost of implementing strategy r_l, then this budget is an upper bound. For the entire set of interdependent infrastructure and industry sectors, if at most budget b is available, then Eq. (13) limits a fixed budget

$$\sum_{l=1}^{m} g_l(r_l) \le b \tag{13}$$

The collection of Eqs. (10), (11), and (13) results in the resource allocation optimization problem in Eq. (14)

$$\begin{aligned} \max_{c_l^\star, r_l} \quad & \frac{\sum_{i=1}^n \sum_{l=1}^m x_i d_{il}^\star (c_{l,\max}^\star - c_l^\star)}{\sum_{i=1}^n \sum_{l=1}^m x_i d_{il}^\star c_{l,\max}^\star} \\ \text{s.t.} \quad & c_l^\star = f_l(c_{l,\max}^\star, r_l), \quad \forall\ l \in \{1, 2, \ldots, m\} \\ & \sum_{l=1}^m g_l(r_l) \le b \\ & g_l(r_l) \ge 0, \quad \forall\ l \in \{1, 2, \ldots, m\} \end{aligned} \tag{14}$$

Eq. (14) represents a generalized formulation of the resource allocation to maximize absorptive capacity. The functional forms of $f_l(\cdot)$ and $g_l(\cdot)$ govern the solution to the absorptive capacity planning problem. For macrolevel planning, the r_l value might denote the amount of capital that can be invested in purchasing and substituting for the lost demand ($c_l^\star$). Assuming $c_{l,\max}^\star$ is the maximum economic loss in industry sector l, Eq. (15) would govern how planning for absorptive capacity can improve $c_l^\star$, where α_l is a measure of the effectiveness of investment r_l, which also shows the return for substituting for lost demand for sector l. The inclusion of α_l into the absorptive capacity enhancement calculation in Eq. (15) is motivated by Barker and Santos (2010a) and Jonkeren and Giannopoulos (2014)

$$c_l^\star = c_{l,\max}^\star e^{-\alpha_l r_l} \tag{15}$$

For this special case, the absorptive capacity planning optimization problem can be written as Eq. (16), given that Eq. (15) is a strict equality constraint. Note that r_l represents an investment made to improve absorptive capacity; therefore, the sum of the cost of strategy r_l must satisfy the budget constraint

$$\begin{aligned} \max_{r_l} \quad & \frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}(c_{l,\max}^{\star} - c_{l,\max}^{\star} e^{-\alpha_l r_l})}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star} c_{l,\max}^{\star}} \\ \text{s.t.} \quad & \sum_{l=1}^{m} g_l(r_l) \le b \\ & g_l(r_l) \ge 0, \quad \forall\ l \in \{1, 2, \ldots, m\} \end{aligned} \tag{16}$$

Note that the duration of disruption of the infrastructure component impacts system performance, and a lengthy duration of disruption of a rather noncritical component might result in a considerable economic loss. However, the focus of this paper is on optimizing the allocation of limited resources that leads to an improved ability to withstand a disruption prior to its occurrence, as measured with multi-industry inoperability. In this paper, the model prioritizes industry sectors according to their criticality for the entire economy considering economic interdependency. The proposed model captures the unsatisfied demands together with their economic value in terms of the maximum loss (demand perturbation) to be avoided. For example, due to a port closure, the undelivered demand in each industry (e.g., food) multiplied by its effect on the economy of that corresponding industry could be considered as the maximum demand perturbation. In general, the duration of port closure and frequency of the closures would only affect the maximum demand perturbation proportionally for all the industries under study. As such, the model captures these two attributes of provisional disruptions. The model proposes a proactive resource allocation strategy at a strategic and tactical level, but not necessarily an operational level, meaning that the model allocates resources to multiple industries before a disruptive event (i.e., strategic level) and not during the disruption or dynamically after the disruption, which changes the allocation procedure immediately after the models sees the changes in the behavior of disruptive events (i.e., operational level). The maximum demand perturbation could be modeled by multiplying the average port closure frequency and the average duration of the closure such that the average port closure duration is sufficiently long [e.g., Pant and Barker (2011) studied a two-week closure with the IIM].

Decision-Making Under Uncertainty

Decision makers with interdependent economic impacts in mind and planning for absorptive capacity to harden industries facing disruption must consider an uncertain environment (e.g., relationships among industries after a disruption).

In this paper, data uncertainty in the integrated model in Eq. (16), consisting of data used to parameterize the IIM and resource allocation, is considered. As the coefficients of the $\mathbf{A}^{\star}$ matrix derived from the technical coefficient matrix $\mathbf{A}$, they are subject to uncertainties arising from the interindustry data collection efforts by the BEA. The BEA collects annual input-output records for a group of 15 aggregated industries and more detailed records for 65 industries every 5 years. As the $\mathbf{x}$ vector is derived from the same BEA data, it is prone to the same uncertainties as $\mathbf{A}^{\star}$. Hence, the economic input-output model, and subsequently the IIM, is prone to uncertainties arising from parameterizing interdependency coefficients matrix $\mathbf{A}$ (and $\mathbf{A}^{\star}$) and $\mathbf{x}$ vector of total output because of statistical errors in compiling massive data bases and the variant nature of these parameters over time (Bullard and Sebald 1977; West 1986). Assuming the values of matrix $\mathbf{A}^{\star}$ are deterministic and time invariant, the derivation from the accurate data can cause the violation of this assumption. Therefore, Barker and Haimes (2009) developed an approach to evaluate the uncertainty in infrastructure interdependencies, minimizing the sensitivity of infrastructure interdependency parameters according to unspecified substitution changes. The inexactness in quantifying the effectiveness of investments within the resource allocation model should also be recognized (MacKenzie and Zobel 2016). Hence, the optimization model formulated in Eq. (16) contains epistemic data uncertainty (Pate-Cornell 1996) in the estimation of (1) the $\mathbf{A}^{\star}$ matrix and magnitude of $\mathbf{x}$ vector; and (2) α_l as the measure of the effectiveness of investment r_l in industry l.

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

We propose a robust formulation of the optimization problem of Eq. (16). This robust formulation is shown in Eq. (17), where D, X, and Ψ are uncertainty sets that contain more anticipated realizations of respective matrices and vectors. It is assumed that the sets D and X contain bounded random variations (e.g., $\pm 5\%$) of the values of $\mathbf{D}^{\star}$ and $\mathbf{x}$, respectively. A triangular distribution represents the set Ψ

$$\begin{aligned} \max \quad & f \\ \text{s.t.} \quad & \left[\frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}(c_{l,\max}^{\star} - c_{l,\max}^{\star} e^{-\alpha_l r_l})}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star} c_{l,\max}^{\star}}\right] \ge f \\ & \sum_{l=1}^{m} g_l(r_l) \le b \\ & g_l(r_l) \ge 0, \quad \forall\ l \in \{1, \ldots, m\} \\ & D^{*} \in D, x \in X, \alpha \in \Psi \end{aligned} \tag{17}$$

The nonlinearity and stochasticity of the proposed model make it difficult to solve analytically. As such, rather than guaranteeing a certain level of absorptive capacity, we want to make sure that the proposed model suggests a resource allocation set such that the probability that maximum absorption capacity (i.e., the disruptions have minimum effect on the system performance) is reached, $\Pr\left(\left[\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}(c_{l,\max}^{\star} - c_{l,\max}^{\star} e^{-\alpha_l r_l}) / \sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star} c_{l,\max}^{\star}\right] \ge f\right)$, is equal or greater than $1 - \varepsilon$ for small $\varepsilon > 0$. The term ε is referred to as value-at-risk in portfolio optimization and has been widely used in "soft" robust optimization (Shapiro et al. 2009; Ben-Tal et al. 2009; Rockafellar and Uryasev 2000). The final formulation is presented in Eq. (18)

$$\begin{aligned} \max \quad & f \\ \text{s.t.} \quad & \Pr\left(\left[\frac{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star}(c_{l,\max}^{\star} - c_{l,\max}^{\star} e^{-\alpha_l r_l})}{\sum_{i=1}^{n}\sum_{l=1}^{m} x_i d_{il}^{\star} c_{l,\max}^{\star}}\right] \ge f\right) \ge 1 - \epsilon \\ & \sum_{l=1}^{m} g_l(r_l) \le b \\ & g_l(r_l) \ge 0, \quad \forall\ l \in \{1, \ldots, m\} \\ & D^{*} \in D, x \in X, \alpha \in \Psi \end{aligned} \tag{18}$$

Illustrative Example: Inland Waterway Port Infrastructure Disruption

The proposed planning model for absorptive capacity is applied to a case study of the Port of Catoosa in Tulsa, Oklahoma. The Port of Catoosa is connected to the US inland waterway network through the McClellan-Kerr Arkansas River Navigation System, which is part of the Mississippi River Navigation System. There are approximately 70 companies using the port and an annual freight volume of 2.2 million tons is sent and received through the port (US Army Corps of Engineers 2011; Tulsa Port of Catoosa 2011). As defined by the North American Industry Classification System (NAICS), 62 industry sectors operate in Oklahoma, therefore the $\mathbf{A}^{\star}$ matrix regionalized for Oklahoma is 62×62. We focus on six industry sectors, shown in Table 1, which represent the port's largest exporters in terms of commodity flows due to high trade figures (Tulsa Port of Catoosa 2011). This study focuses on improving the absorptive capacities of these six industry sectors. It is assumed that a port disruption (a two-week port closure) is sufficiently local when, without loss of generality, no other industry sectors are directly impacted. It is further assumed that the occurrence of natural disaster is infrequent, and the analyses do not account for expected losses given some frequency of disruption (although such could be included in future work).

The exports through the Port of Catoosa contribute to the external demand of the industries in Oklahoma. As such, in case of a disaster at the port resulting in the loss of exports, there is a demand perturbation in the industries that use the port. Because of the interdependence among industries, the cascading of the demand perturbations causes losses to all the other state industries. Assuming that, in the case of a disruptive event, the only losses in the state economy are because of the loss of exports through the port, we can obtain estimates of the maximum demand perturbations ($c^{\star}_{l,\max}$) for the six primary industries using the port. These are found for each industry as the ratio of that industry's mean estimate of exports to its total economic output, which are all provided in Table 2. It is further assumed that industries not using the port have zero demand perturbations, although they could suffer from interdependent inoperability.

Table 1. Six primary industries using the Port of Catoosa, along with their NAICS codes

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

A policymaker caring about the economy of the state of Oklahoma [e.g., The Oklahoma Department of Transportation (ODOT)] may seek the best way to allocate a limited budget to individual industries allowing them to invest in absorptive capacity improvements to avoid the maximum demand perturbation during the port closure. Depending on the industry faced with the disruptive event, this resource could describe: (1) maintaining additional inventory to maintain productivity, and (2) setting short-term coordination contracts with distributors to be ready for alternative transportation modes other than the port.

The model assumes that allocating resources reduces the impact exponentially. As more resources are allocated to an industry, the impacts on an industry decline at a constantly decreasing rate, and investing an additional dollar to reduce risk returns less benefit than investing the first dollar. For each directly impacted industry, the exponential function, shown in Eq. (16) requires estimating an investment effectiveness parameter, α_l. This parameter can be assessed if r_l, the amount of resources needed to reduce the direct impacts on industry l by a fraction $c^{\star}_l / c^{\star}_{l,\max}$, is known or can be estimated, since $\alpha_l = -[\log(c^{\star}_l / c^{\star}_{l,\max})/r_l]$. While the value of α_l is always non-zero and positive with no upper bound, it is expected that α_l would be small for large-scale disruptions where millions of dollars are necessary to reduce the impact.

Table 3 lists parameter estimates for the effectiveness of investments (α_l) in planning for absorptive capacity in different industries considering the consequences on reducing the maximum demand perturbation by 50% (i.e., setting $c^{\star}_l / c^{\star}_{l,\max} = 0.5$). Food and beverage products would be affected dramatically by the closure of the Port of Catoosa considering estimates for the cost per ton-mile for a barge at \$0.97, compared to \$2.53 for rail, and \$5.35 for trucking (Arkansas Waterway Commissions 2014), together with the distances to the general customers for the products of this industry, it is assumed that on average \$7 million should be invested to avoid the maximum demand perturbation in this industry by 50% (MacKenzie et al. 2012; Aydin and Shen 2012; Richards and Patterson 1999). Direct impacts for petroleum and coal products is much less than food and beverage products, but the nature of this industry's products makes it difficult to look for alternative transport modes. Also, long-term investments in increasing domestic demand by developing refining facilities, pipelines, and alternate transportation infrastructures could be effective and result in a higher absorptive capacity (Davarzani et al. 2011; Halkin et al. 2017). As such, α_2 is calculated assuming that an almost \$5 million investment is needed to decrease the maximum demand perturbation in petroleum industries by half (Alizadeh and Nomikos 2004; Nealer et al. 2011). The investment effectiveness for the other four industries are estimated considering the maximum loss in each industry and the options to increase the absorptive capacity with potential contracts for alternative transportation modes.

Table 2. Maximum demand perturbation for the major industries using the Port of Catoosa in 2007 (output and exports given in million USD)

Industry name	Exports	Output	$c^{\star}_{l,\max}$
Food, beverage, and tobacco products	140.0	5,578.5	0.0251
Petroleum and coal products	57.0	12,644.0	0.0045
Chemical products	89.0	1,327.3	0.0671
Nonmetallic mineral products	3.0	2,026.2	0.0015
Machinery	108.0	7,174.4	0.0151
Miscellaneous manufacturing	6.0	746.6	0.0080

Table 3. Estimates for the cost-effective parameter α_l (given as per million USD)

l	Industry name	α_l
1	Food, beverage, and tobacco products	0.046
2	Petroleum and coal products	0.063
3	Chemical products	0.342
4	Nonmetallic mineral products	0.201
5	Machinery	0.084
6	Miscellaneous manufacturing	0.426

Planning for Absorptive Capacity

The proposed model in Eq. (16) is implemented to optimize the budget allocation among the six important industries that trade through the Port of Catoosa. Four different total budget amounts are considered for allocations across the six industries: \$10 million, \$20 million, \$30 million, and \$40 million. To solve the model, we use the Frontline Solvers simulation optimization plug-in solver engine, which is an optimization and simulation application for Microsoft Excel (Olson and Wu 2013).

Table 4 shows the results from solving Eq. (16), in terms of the budgets r_l allocated to individual sectors. We see that to maximize the absorptive capacity of the whole interdependent economy, certain budget allocations will give the following results: (1) at the smallest budget allocation of \$10 million, most of the resources are distributed to miscellaneous manufacturing (339) and chemical products (325); (2) as the budget allocation is increased toward \$40 million, the resources get distributed toward food and beverage and tobacco products (311) and machinery (333); (3) petroleum and coal products (324) comparatively require some resource allocations when budgets are increased to \$30 million and beyond; and (4) nonmetallic mineral products (327) comparatively require very little resource allocations. These results make sense because, based on Table 2 data, food and beverage and tobacco products (311) and machinery (333) are the two highest exporters through the port, so to progressively maximize the absorptive capacity of the economy most of the budget allocations will be distributed toward restoring economic flows in these sectors. Miscellaneous manufacturing (339) and chemical products (325) have high initial resource allocation values because the cost effectiveness parameters α_l from Table 3 are high. But this means there is a fast stabilization of absorptive capacities in these sectors at the initial investment of \$10 million, and subsequently, these sectors require smaller increments of the resource allocations to further maximize the absorptive capacity of the economic system. Table 5 confirms this conclusion above, as indicated by the values of the absorptive capacities of individual sectors as budget allocations are increased.

Also shown in Table 5 are the values of the total economic losses avoided and the level of absorptive capacity achieved [value of the objective function of Eq. (16)] corresponding to each level of budget allocation. We see that if no budget allocations were made then, there is an economic loss of \$95.2 million to the six industries, which is estimated from Table 5 by summing the economic loss values for these sectors. Overall, the whole economy has a loss of \$146.6 million. These results show the interdependent effects of the IIM in Eq. (3). A budget allocation of \$10 million results in decreasing economic losses by \$37.9, which is a 25.8% restoration of absorptive capacity. Similarly, a budget allocation of \$40 million decreases the economic losses by \$84.8, thereby restoring absorptive capacity by 57.8%.

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

As shown in Table 5, investment of \$30 million to harden the five industries among the six most important to the port can avoid the maximum economic loss in Oklahoma by up to 50%, and it indirectly protects nonmetallic mineral products (327), although the policy maker does not devote resources directly to this industry. Furthermore, for example, nearly \$40 million in economic losses across the Oklahoma economy can be avoided with a \$10 million investment in absorptive capacity in the six key industries, according to the model.

Fig. 4 shows the extent, as a ratio between 0 and 1, to which each industry and the Oklahoma economy are able to absorb shocks from a port disruption by allocating a defined amount of budget to harden the most important industries in the area. In comparison to the results of Table 5, where the magnitudes of losses based on budget allocations are shown, this result shows that the level absorptive capacity achieved by the chemical products (325) sector is the highest even though its allocated budget might be lower.

Table 4. Resource allocation for absorptive capacity in different industries (in million USD)

Industry name	Resources allocated to each industry for each total budget			
	10	20	30	40
Food, beverage and tobacco products	0.31	5.88	10.95	14.92
Petroleum and coal products	0.00	0.00	0.92	3.81
Chemical products	3.88	4.63	5.31	5.84
Nonmetallic mineral products	0.00	0.00	0.00	0.00
Machinery	2.78	5.85	8.64	10.82
Miscellaneous manufacturing	3.03	3.63	4.18	4.61

Table 5. Economic loss under different total budget plans (budgets and losses in million USD)

Industry name	Economic loss (no investment)	Economic losses for each total budget			
		10	20	30	40
Food, beverage, and tobacco products	25.90	25.38	19.68	15.54	12.95
Petroleum and coal products	12.59	11.71	11.46	10.70	8.94
Chemical products	16.46	4.61	3.62	2.96	2.47
Nonmetallic mineral products	1.04	0.95	0.87	0.81	0.77
Machinery	20.32	16.05	12.40	9.96	8.33
Miscellaneous manufacturing	18.88	7.74	6.23	4.91	4.15
Total loss in port sectors	95.19	66.44	54.26	44.88	37.61
Total macroeconomic loss	146.63	108.74	88.88	73.98	61.79
Total economic loss avoided	—	37.90	57.70	72.60	84.80
Total absorptive capacity (ratio)	—	0.26	0.39	0.49	0.58

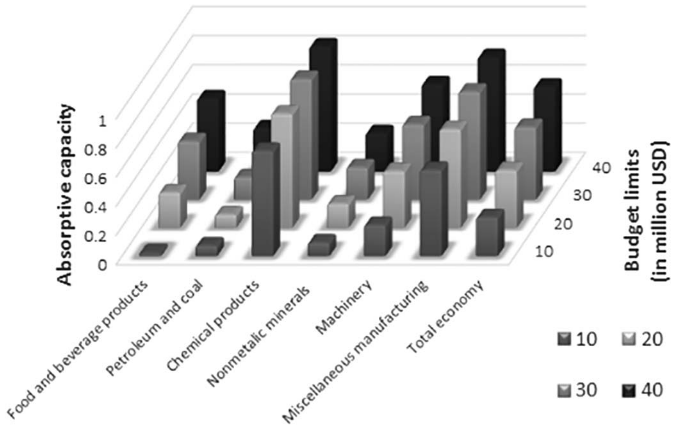

Fig. 4. Absorptive capacity at different budget limits.

Decision-Making Under Uncertainty

As discussed previously, epistemic uncertainty in estimating $\mathbf{A}^\star$ and α_l should be accounted for in this paper. Small amounts of perturbations are considered when modeling data uncertainties in $\mathbf{x}$ and $\mathbf{D}^\star$. It is assumed that the elements insets X and D related to the six industries contain bounded random variations to the amount of $\pm 5\%$ of the (deterministic) values of $\mathbf{x}$ and $\mathbf{D}^\star$, respectively. Furthermore, a probabilistic treatment considering the optimistic, pessimistic, and most likely estimates of α_l with a triangular distribution is assumed to model uncertainty in the investment effectiveness for industry l. The parameters of these triangular distributions are shown in Table 6. We model the uncertainty in this problem and obtain an exact solution using Frontline Solvers, an optimization and simulation application for Microsoft Excel. This application makes it easy to replicate simulation runs and includes the ability to correlate variables, expeditiously select from standard distributions, aggregate and display output, and other useful functions (Olson and Wu 2013). The solution is bounded by the total available budget, and both deterministic and stochastic solutions are shown in Table 7.

Table 6. Probabilistic treatment estimating the cost-effective parameter α_l

		α_l		
l	Industry name	Min	Mode	Max
1	Food, beverage, and tobacco products	0.024	0.046	0.057
2	Petroleum and coal products	0.040	0.063	0.070
3	Chemical products	0.100	0.342	0.400
4	Nonmetallic mineral products	0.090	0.201	0.300
5	Machinery	0.060	0.083	0.090
6	Miscellaneous manufacturing	0.200	0.426	0.500

Table 7. Total economic loss (in million USD) considering deterministic and epistemic data uncertainty for different budget amounts (in million USD)

	Total economic loss				
		Epistemic uncertainty			
Budget	Deterministic	Mean	SD	5th percentile	95th percentile
10	108.74	111.49	3.00	107.21	116.95
20	88.88	93.27	3.22	88.55	99.08
30	73.98	78.93	3.60	73.50	85.45
40	61.79	67.14	3.79	61.53	73.74

Table 7 and Fig. 5 show how epistemic data uncertainty simulated with 1,000 replications affects the total economic losses resulting from each total budget, which are allocated based on the solutions of Eq. (16). The differences between 5th and 95th percentiles of simulated results is \$9 and \$12 million in the cases of the four different budget limits. Also, as the standard deviation shows, the amount of variation or data dispersion because of the uncertainty is at least \$3 million, highlighting the importance of accounting for uncertainty in decision-making. The budget allocation based on the deterministic model cannot address the epistemic uncertainty in the model. Hence, we consider the data uncertainty in decision-making for allocating the limited budget to harden the six industries within the state of Oklahoma.

Implementing the proposed soft-robust optimization model in Eq. (18), $\varepsilon = 0.05$ is considered to guarantee an absorbability that holds with probability of $(1 - \varepsilon = 95\%)$. When comparing the resource allocation resulting from the data uncertainty shown in Table 8 with the results from the deterministic model shown in Table 4, the allocation differences are generally less than 10%. Some exceptions include food and beverage and tobacco products (311), which experience a 100% decrease when the total budget is \$10 million and subsequently has lesser budget allocations compared to the values in Table 4. Similarly, petroleum and coal products (324) encounter decreases in allocated resources, which vary for different total budget amounts. Comparatively, chemical products (325), miscellaneous manufacturing (339), and machinery (333) see increases in budget allocations in that order. These changes, though small, show how uncertainty can alter the resource allocations.

Fig. 6 shows the 95% confidence interval estimates for total losses in the Oklahoma economy expected when each total budget is allocated across the six industries.

A measure of the effectiveness of investment α_l is considered to monitor the effects of changes in the data uncertainty of budget allocation. Fig. 7 illustrates the changes in the resulting allocated budget to each industry when the interval in probabilistic treatment of α_l is increased by 25%, 50%, and 75%. These three incremental levels of uncertainty are deployed by changing the upper and lower limits shown in Table 6, while the mode values are kept constant. The percentage of changes in budget allocation when compared with the results of the deterministic model for different budget limits are plotted. As shown in Fig. 7, the different behaviors in the percentage of the changes in allocating budget to the six industries are monitored based on the total budget limits and the magnitude of the change in the uncertainty interval. For example, significant decreases are seen in the budget that should be allocated to food and beverage and tobacco products (311) when the total budget is less than \$20 million, which is comparable to the results from the deterministic model. Relatively small changes are seen for the allocated budget to chemical products (325). Also, a recognizable change exists in petroleum and coal products (324) when the total budget limit is more than \$20 million, where an increase in the uncertainty interval decreases the budget that should be allocated. In general, it can be seen that the larger uncertainty interval for investment effectiveness caused more changes in budget allocation for higher budget limits.

Concluding Remarks

Freight transportation infrastructure plays an important role as a facilitator of economic productivity by connecting industries of multiple regions. Large-scale disruptive events can cause failures within the system that propagate through the multiple interconnected industries. Investing in hardening both the infrastructure

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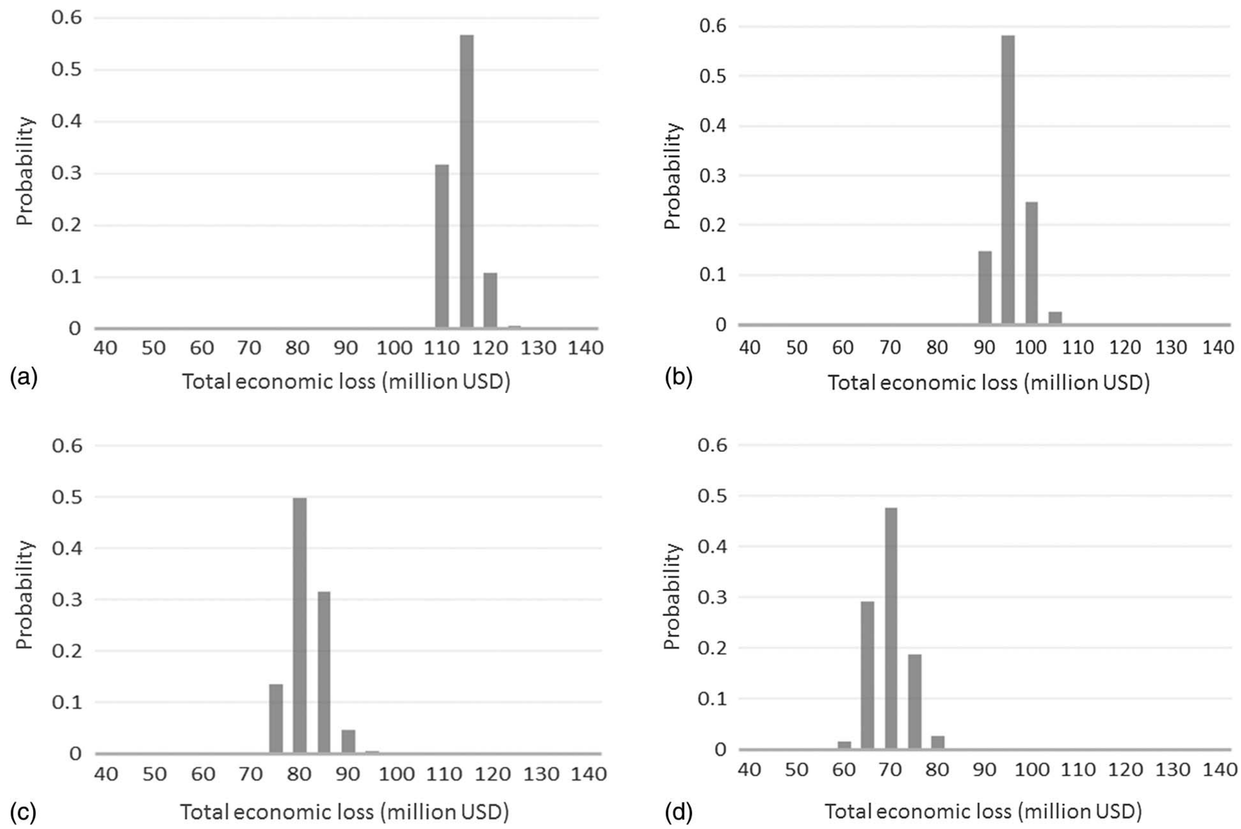

Fig. 5. Distributions of total economic loss considering epistemic data uncertainty given total budgets of (a) \$10 million; (b) \$20 million; (c) \$30 million; and (d) \$40 million.

Table 8. Resource allocation for absorptive capacity in different industries considering uncertainty (in million USD)

	Resources allocated to each industry for each total budget			
Industry name	10	20	30	40
Food, beverage, and tobacco products	0.00	5.34	10.71	14.56
Petroleum and coal products	0.00	0.00	0.23	3.07
Chemical products	4.10	4.96	5.83	6.43
Nonmetallic mineral products	0.00	0.00	0.00	0.00
Machinery	2.71	5.84	8.73	10.98
Miscellaneous manufacturing	3.19	3.85	4.50	4.95

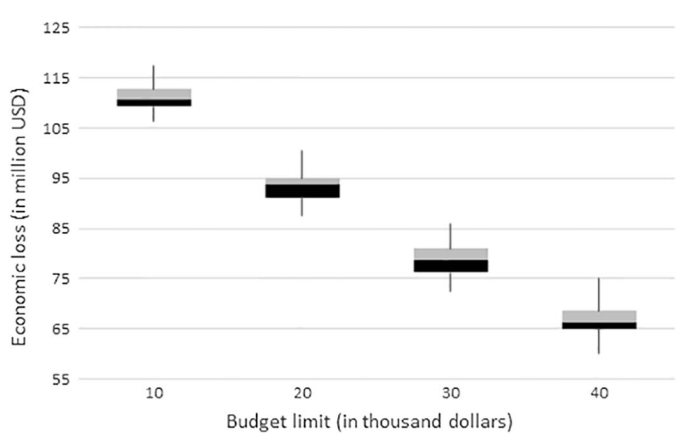

Fig. 6. 95% confidence interval estimates of total economic loss (million USD) under different budget limits (thousand USD).

(e.g., backup equipment) and industries themselves (e.g., on hand inventory) can lessen the effects of disruptions. The interdependent nature of industries must be considered when evaluating such resource allocation. This paper discusses modeling and analysis on the absorptive capacity of resource allocation.

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

The proposed modeling and analysis are implemented in a case study developed from the six important industries at the Port of Catoosa that use the inland waterway to send out commodities to their consumers out of the state of Oklahoma. Results show how increasing the budget limit affects allocated budget to each industry. Although miscellaneous manufacturing (339) and chemical products (325) receive the largest share with the \$10 million budget, food and beverage and tobacco products (311) and machinery (333) receive the largest share as the budget allocation is increased to \$40 million. We see that when considering bounded random variations to the amount of $\pm 5\%$ of the (deterministic) values of $\mathbf{x}$ and $\mathbf{D}^{\star}$ together with a probabilistic treatment [i.e., incorporating epistemic uncertainty in the calculation of Eq. (18)], the

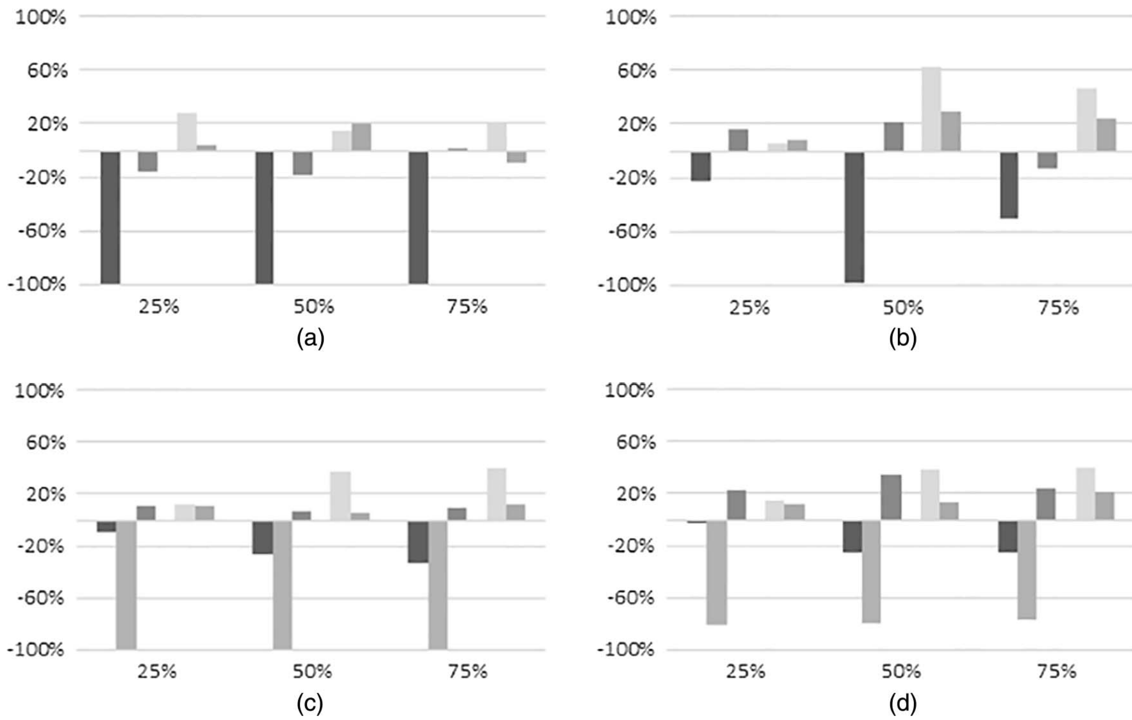

Fig. 7. Percentage of changes in budget allocation with increasing interval width (25%, 50%, and 75%) for the probabilistic treatment of the investment effectiveness parameter α_l given total budgets of (a) \$10 million; (b) \$20 million; (c) \$30 million; and (d) \$40 million.

optimistic, pessimistic, and most likely estimates of α_l cause dramatic variations in the economic loss as a result of the allocated budget. Also, analysis done on the measure of effectiveness shows that when the interval in the probabilistic treatment of α_l is increased by 25%, 50%, and 75%, the changes in the allocated budget varies in different budget limits. For example, while food and beverage and tobacco products (311) experience a significant decrease in the allocated budget when the total budget is less than \$20 million, it faces at most a 30% decrease when the total budget is \$40 million.

The real-world application of this work lies in informing a central planner to invest more effectively in port resilience to maintain the continuity of service for businesses using the docks. The Port of Catoosa, where our case-study applies, is a public entity overseen by a nine-member board, representing the central planner in our case (Business View Magazine 2016). The investment into the macroeconomic sectors here refers to the investment into port dock operations that facilitate a faster continuity of service flowing through the port for the businesses associated with these sectors. For example, the freight of miscellaneous manufacturing and machinery is handled at the General Dry Cargo dock, which handles the largest tonnage in the port [see Pant et al. (2015) for a variety of tonnages]. Hence, preferring these sectors for different levels of investment reflects the importance of the General Dry Cargo dock for the real-world operations of the port. Similarly, the importance of other sectors like chemical products and food and beverage and tobacco products emerges from the significance of Liquid Bulk and Grains docks, respectively. It is acknowledged here that individual businesses that depend on the port might have different preferences relative to the port operators, whose decisions are informed by the larger-scale macroeconomic impacts on the state and regional economy. The Port of Catoosa is a major industrial hub in the Tulsa metropolitan statistical area (MSA), which contributes to 33.4% of the economy of the state of Oklahoma (Tulsa Regional Chamber 2018); therefore, the options here are aimed at benefiting the wider state and regional economy through the port. Although it can be said that for small tonnage disruptions individual businesses can use alternative suppliers and options such as road and railway transport, when the tonnage disruptions are substantial, their interests would align with the port's as both can benefit from the business preference for the cheaper mode of barge transport. Evidence shows that the port received \$6.25 million in 2011 through the federally funded Transportation Infrastructure Generating Economic Recovery (TIGER) grant [now called Better Utilizing Investments to Leverage Development (BUILD)] (DoT 2018) and additional investments through private companies, which resulted in the port investing \$13 million in renovating a 45-year old dock (Business View Magazine 2016). This suggests an interest of aligned public and private initiatives in the improvement of port operations. The analysis presented here aims to inform such spending decisions.

The proposed model can be implemented in a freight infrastructure network, and the multiregional impacts of the disruption can be considered in both modeling the failure propagation and investing for absorptive capacity. Further developments of this work will explore such options.

References

Alizadeh, A. H., and N. K. Nomikos. 2004. "Cost of carry, causality and arbitrage between oil futures and tanker freight markets." *Transp. Res. Part E* 40 (4): 297–316. https://doi.org/10.1016/j.tre.2004.02.002.

Arkansas Waterway Commissions. 2014. "Arkansas Waterway Commissions—Interactive access to website." Accessed December 31, 2014. http://waterways.arkansas.gov/.

Arnold, B., C. Cammarata, D. Farmer, K. Kowalewski, F. Ladipo, M. Lasky, and D. Moore. 2006. *The economic costs of disruptions in container shipments*. Washington, DC: Congressional Budget Office.

Aydin, S. G., and G. Shen. 2012. "A retro-analysis of I-40 bridge collapse on freight movement in the U.S. highway network using GIS and assignment models." *Int. J. Transp. Sci. Technol.* 1 (4): 379–397. https://doi.org/10.1260/2046-0430.1.4.379.

Barker, K., and Y. Y. Haimes. 2009. "Uncertainty analysis of interdependencies in dynamic infrastructure recovery: Applications in risk-based decision making." *J. Infrastruct. Syst.* 15 (4): 394–405. https://doi.org/10.1061/(ASCE)1076-0342(2009)15:4(394).

Barker, K., J. E. Ramirez-Marquez, and C. M. Rocco. 2013. "Resilience-based network component importance measures." *Reliab. Eng. Syst. Saf.* 117 (1): 89–97. https://doi.org/10.1016/j.ress.2013.03.012.

Barker, K., and J. R. Santos. 2010a. "A risk-based approach for identifying key economic and infrastructure sectors." *Risk Anal.* 30 (6): 962–974. https://doi.org/10.1111/j.1539-6924.2010.01373.x.

Barker, K., and J. R. Santos. 2010b. "Measuring the efficacy of inventory with a dynamic input-output model." *Int. J. Prod. Econ.* 126 (1): 130–143. https://doi.org/10.1016/j.ijpe.2009.08.011.

Ben-Tal, A., L. Ghaoui, and A. Nemirovski. 2009. *Robust optimization*. Princeton, NJ: Princeton University Press.

Bienstock, D., and S. Mattia. 2007. "Using mixed-integer programming to solve power grid blackout problems." *Discrete Optim.* 4 (1): 115–141. https://doi.org/10.1016/j.disopt.2006.10.007.

Bullard, C. W., III, and A. V. Sebald. 1977. "Effects of parametric uncertainty and technological change in input-output models." *Rev. Econ. Stat.* 59 (1): 75–81. https://doi.org/10.2307/1924906.

Business View Magazine. 2016. "Tulsa Port of Catoosa—Where the barges are running." Accessed September 21, 2018. https://businessviewmagazine.com/the-tulsa-port-of-catoosa-where-the-barges-are-running/.

Bye, P., L. Yu, S. H. Shivastava, and S. Van Leeuwen. 2013. Vol. 753 of *A pre-event recovery planning guide for transportation*. Washington, DC: Transportation Research Board.

Çelik, M., Ö. Ergun, and P. Keskinocak. 2015. "The post-disaster debris clearance problem under incomplete information." *Oper. Res.* 63 (1): 65–85. https://doi.org/10.1287/opre.2014.1342.

Darayi, M., K. Barker, and J. R. Santos. 2017. "Component importance measures for multi-industry vulnerability of a freight transportation network." *Net. Spatial Econ.* 17 (4): 1111–1136. https://doi.org/10.1016/j.scient.2011.02.001.

Davarzani, H., S. H. Zegordi, and A. Norrman. 2011. "Contingent management of supply chain disruption: Effects of dual or triple sourcing." *Sci. Iranica* 18 (6): 1517–1528. https://doi.org/10.1016/j.scient.2011.02.001.

DHS (Department of Homeland Security). 2013. *National infrastructure protection plan: Partnering for critical infrastructure security and resilience*. Washington, DC: US Dept. of Homeland Security.

DoT (Department of Transport). 2018. "BUILD discretionary grants." Accessed September 21, 2018. https://www.transportation.gov/BUILDgrants.

Fialkoff, M. R., O. A. Omitaomu, S. K. Peterson, and M. A. Tuttle. 2017. "Using geographic information science to evaluate legal restriction on freight transportation routing in disruptive scenarios." *Int. J. Crit. Infrastruct. Prot.* 17 (1): 60–74. https://doi.org/10.1016/j.ijcip.2016.12.001.

Haefner, L., R. Goodwin, and L. Porrello. 1996. "The great flood of 1993: Impacts on waterborne commodity flow, rail transportation, and surrounding region." In *Proc., Semisesquicentennial Transportation Conf.* Ames, IA: Center for Transportation Research and Education.

Halkin, A., V. Skrypin, E. Kush, K. Vakulenko, and V. Dolia. 2017. "Invest approach to transportation services cost formation." *Procedia Eng.* 178 (1): 435–442. https://doi.org/10.1016/j.proeng.2017.01.086.

Ham, H., T. J. Kim, and D. Boyce. 2005. "Implementation and estimation of a combined model of interregional, multimodal commodity shipments and transportation network flows." *Transp. Res. Part B* 39 (1): 65–79. https://doi.org/10.1016/j.trb.2004.02.005.

Hosseini, S., and K. Barker. 2015. "Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports." *Comput. Ind. Eng.* 93 (Mar): 252–266. https://doi.org/10.1016/j.cie.2016.01.007.

Hosseini, S., K. Barker, and J. E. Ramirez-Marquez. 2016. "A review of definitions and measures of system resilience." *Reliab. Eng. Syst. Saf.* 145 (Jan): 47–61. https://doi.org/10.1016/j.ress.2015.08.006.

Jonkeren, O., and G. Giannopoulos. 2014. "Analysing critical infrastructure failure with a resilience inoperability input–output model." *Econ. Syst. Res.* 26 (1): 39–59. https://doi.org/10.1080/09535314.2013.872604.

Kujawski, E. 2006. "Multi-period model for disruptive events in interdependent systems." *Syst. Eng.* 9 (4): 281–295. https://doi.org/10.1002/sys.20057.

Lempert, R. J., and D. G. Groves. 2010. "Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American West." *Technol. Forecasting Social Change* 77 (6): 960–974. https://doi.org/10.1016/j.techfore.2010.04.007.

Leontief, W. W. 1986. *Input-output economics*. Oxford, UK: Oxford University Press.

MacKenzie, C. A., K. Barker, and F. H. Grant. 2012. "Evaluating the consequences of an inland waterway port closure with a dynamic multiregional interdependency model." *IEEE Trans. Syst. Man Cybern. Part A: Syst. Humans* 42 (2): 359–370. https://doi.org/10.1109/TSMCA.2011.2164065.

MacKenzie, C. A., and C. W. Zobel. 2016. "Allocating resources to enhance resilience, with application to superstorm sandy and an electric utility." *Risk Anal.* 36 (4): 847–862. https://doi.org/10.1111/risa.12479.

Nealer, R., C. L. Weber, C. Hendrickson, and H. S. Matthews. 2011. "Modal freight transport required for production of US goods and services." *Transp. Res. Part E* 47 (4): 474–489. https://doi.org/10.1016/j.tre.2010.11.015.

Olson, D., and D. Wu. 2013. "The impact of distribution on value-at-risk measures." *Math. Comput. Modell.* 58 (9–10): 1670–1676. https://doi.org/10.1016/j.mcm.2011.06.053.

Pant, R., and K. Barker. 2011. On robust decision-making in interdependent economic and infrastructure systems. In *Proc., 11th Int. Conf. on Applications of Statistics and Probability in Civil Engineering*. Boca Raton, FL: CRC Press.

Pant, R., K. Barker, F. H. Grant, and T. L. Landers. 2011. "Interdependent impacts of inoperability at multi-modal transportation container terminals." *Transp. Res. Part E: Logist. Transp.* 47 (5): 722–737.

Pant, R., K. Barker, and T. L. Landers. 2015. "Dynamic impacts of commodity flow disruptions in inland waterway networks." *Comput. Ind. Eng.* 89 (Nov): 137–149. https://doi.org/10.1016/j.cie.2014.11.016.

Pant, R., K. Barker, and C. W. Zobel. 2014. "Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors." *Reliab. Eng. Syst. Saf.* 125 (1): 92–102. https://doi.org/10.1016/j.ress.2013.09.007.

Park, J., J. Cho, P. Gordon, J. E. Moore, II, H. W. Richardson, and S. Yoon. 2011. "Adding a freight network to a national interstate input–output model: A TransNIEMO application for California." *J. Transp. Geogr.* 19 (6): 1410–1422. https://doi.org/10.1016/j.jtrangeo.2011.07.019.

Pate-Cornell, M. 1996. "Uncertainties in risk analysis: Six levels of treatment." *Reliab. Eng. Syst. Saf.* 54 (2–3): 95–111. https://doi.org/10.1016/S0951-8320(96)00067-1.

Richards, T. J., and P. M. Patterson. 1999. "The economic value of public relations expenditures: Food safety and the strawberry case." *J. Agric. Resour. Econ.* 24 (2): 440–462.

Rockafellar, R. T., and S. Uryasev. 2000. "Optimization of conditional value-at-risk." *J. Risk* 2 (3): 21–41. https://doi.org/10.21314/JOR.2000.038.

Rose, A. 2004. "Defining and measuring economic resilience to disasters." *Disaster Prev. Manage.* 13 (4): 307–314. https://doi.org/10.1108/09653560410556528.

Rose, A. 2007. "Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions." *Environ. Hazard.* 7 (4): 383–398. https://doi.org/10.1016/j.envhaz.2007.10.001.

Rose, A. 2009. *Economic resilience to disasters*. Community and Regional Resilience Institute (CARRI) Research Rep. 8. Oakridge, TN: CARRI Institute.

Santos, J. R., and Y. Y. Haimes. 2004. "Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures." *Risk Anal.* 24 (6): 1437–1451. https://doi.org/10.1111/j.0272-4332.2004.00540.x.

Shapiro, A., D. Dentcheva, and A. Ruszczynski. 2009. *Lectures on stochastic programming: Modeling and theory.* Philadelphia: SIAM and Mathematical Programming Society.

Shen, G., and S. G. Aydin. 2014. "Origin-destination missing data estimation for freight transportation planning: A gravity model-based regression approach." *Transp. Plann. Technol.* 37 (6): 505–524. https://doi.org/10.1080/03081060.2014.927665.

The White House. 2011. *Presidential policy directive/PPD-8: National preparedness*. Washington, DC: US Dept. of Homeland Security.

Tulsa Port of Catoosa. 2011. "Tulsa Port of Catoosa—Interactive access to website." Accessed December 31, 2011. http://www.tulsaport.com.

Tulsa Regional Chamber. 2018. "2018—Economic profile." Accessed September 21, 2018. http://www.growmetrotulsa.com/sites/default/files/page-attachments/EDD_2018%20EconomicProfile_Low%2005.16.18.pdf.

US Army Corps of Engineers. 2011. "US Army Corps of Engineers—Interactive access to website." Accessed December 31, 2011. http://www.iwr.usace.army.mil/ndc.

Vugrin, E. D., and R. C. Camphouse. 2011. "Infrastructure resilience assessment through control design." *Int. J. Crit. Infrastruct.* 7 (3): 243–260. https://doi.org/10.1504/IJCIS.2011.042994.

West, G. R. 1986. "A stochastic analysis of an input-output model." *Econometrica* 54 (2): 363–374. https://doi.org/10.2307/1913156.

Whitson, J. C., and J. E. Ramirez-Marquez. 2009. "Resiliency as a component importance measure in network reliability." *Reliab. Eng. Syst. Saf.* 94 (10): 1685–1693. https://doi.org/10.1016/j.ress.2009.05.001.