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Multicriteria risk analysis of commodity-specific dock investments at an inland waterway port

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ABSTRACT

Managing risks to critical infrastructure systems requires decision makers to account for impacts of disruptions that render these systems inoperable. This article evaluates dock-specific resource allocation strategies to improve port preparedness by integrating a dynamic risk-based interdependency model with weighted multicriteria decision analysis techniques. A weighted decision analysis technique allows for decision makers to balance widespread impacts due to cascading inoperability with certain industries that are important to the local economy. Further analysis of the relationship between inoperability and expected economic losses is explored per commodity flowing through the port, which allows an understanding of cascading impacts through interdependent industries. Uncertainty is accounted for through the use of probability distributions of total expected loss per industry that encompass the uncertainty of the length of disruption and severity of the impact that is mitigated by alternative strategies. A set of discrete allocations options of preparedness plans is analyzed in a study of the Port of Catoosa in Oklahoma along the Mississippi River Navigation System. The economic loss analysis showed that the integration of multicriteria decision analysis helps in prioritizing strategies according to several criteria such as gross domestic product (GDP) and decision maker risk aversion that are not typically addressed when strategies are prioritized according to the average interdependent economic losses alone.

Introduction and motivation

Critical infrastructure systems, such as electric power networks, telecommunications, and transportation systems, are essential to economic productivity and the functioning of society (Department of Homeland Security [DHS] 2013). When such infrastructure systems are disrupted, widespread inoperability can be felt across many industries that rely on them. The resilience of these infrastructure systems, generally defined as the ability of a system to withstand, adapt to, and recover from a disruptive event (Obama 2013), is an important consideration in infrastructure preparedness planning.

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When investing limited resources to prepare for disruptive events, it is important to understand the relationship between the amount invested and the efficacy of that investment to enhance resilience, as measured across the multiple industries that experience inoperability resulting from a disruptive event such as an attack, accident, natural disaster, or common-cause failure.

In particular, the multimodal transportation system is considered critical due to its centrality in enabling the flow of commodities and commuter traffic. In 2012, the U.S. transportation system transported a daily average of 54 million tons of freight valued at nearly $48 billion (Federal Highway Administration 2014). Currently, over 70% of goods are moved by truck, but there are growing concerns about highway congestion, emissions, and bottlenecks (Government Accountability Office 2013; Margreta et al. 2014). A majority of urban areas are seeing worsened measures of congestion, including the average duration of daily congestion, travel times during peak versus nonpeak periods, and the variability (or unreliability) of travel time (Federal Highway Administration 2015). In 2011, the cost of congestion was estimated at more than $120 billion, or nearly $820 for every commuter in the United States (Schrank et al. 2012), which is primarily calculated from passenger and truck value of lost time and fuel expended and not fully accounting for the cost of delayed freight shipments.

Inland waterway ports play perhaps an underutilized role in the larger multimodal transportation system and have potential as a viable alternative that is less expensive, more fuel efficient, and environmentally friendly (Kruse et al. 2012). Inland waterway barges expend less than a third of the energy, in British thermal units per ton-mile, relative to trucks (Kruse et al. 2009). Recognizing the need to reduce road and rail congestions, the U.S. Maritime Administration, a division of the U.S. Department of Transportation, has called for an investment in inland waterways for general freight movement (U.S. Department of Transportation 2011). Some pressing challenges that prevent inland waterway networks from playing a more significant role in multimodal transportation are aging infrastructure and resulting maintenance delays (American Society of Civil Engineers 2013). However, there are viable scenarios where inland waterway networks are successful and could play an important role in the future growth of the economy (Kruse and Hutson 2010).

The study of the impacts of disruptive events (e.g., natural disasters, attacks, accidents, and other common-cause failures) to inland waterway networks is a relatively underdeveloped area of research compared to highway and railway transport systems and coastal ports (discussed subsequently). Due to their aging infrastructure, inland waterway networks are especially vulnerable to disruptions and in need of investigation. In 2012, the DHS allocated $1.3 billion to the Preparedness Grant Program and distributed over $97 million to the Port Security Grant Program (PSGP) to support increased port-wide risk management (DHS 2012). Risk analysis plays a key role in allocating resources to ports applying to PSGP for funding.

Several studies have addressed port security (Talley and Lun 2012; Trbojevic and Carr 2000) and the impacts of disruptive events at coastal ports (Chang 2000; Yip 2008), but little work addresses such problems at inland ports. Further, economic impact analyses of disruptions to transportation systems primarily deal with highway and railway transport systems (Gordon et al. 2004; Ham et al. 2005a, 2005b; Sohn et al.

2004). Pant et al. (2011) integrated a port operations simulation model with a risk-based interdependency model to quantify the multiregional, multi-industry impacts of disruptions to port operations. MacKenzie, Barker, and Grant (2012) explored the multiregional, multi-industry impacts of shipping recovery options (e.g., finding alternate routes, holding commodities until operability is regained). Pant et al. (2015) evaluated multiregional, multi-industry impacts of dock-specific closures and subsequent recoveries at an inland waterway port. Baroud et al. (2014) integrated the interdependency modeling paradigm with stochastic decision analysis to assess investment strategies, highlighting the relationship between preparedness investment and (i) the probability of a disruptive event, (ii) the severity of the event, (iii) the length of time of recovery, and, ultimately, (iv) the reduction in multi-industry impacts following the event. The disruptive event can be the result of a natural hazard, a human-made attack, or an accident, the occurrence and severity of which are governed by probability distributions. Previous work by Whitman et al. (2015) assessed the dynamic multi-industry impacts of dock-specific investment alternatives, incorporated with multicriteria decision analysis to effectively evaluate risk-based preparedness strategies.

This article builds on previous work by integrating the dock-specific approach from Pant et al. (2015) and the relationship between preparedness investment and multi-industry impact from Baroud et al. (2014) to provide a more tangible assessment of the effect of preparedness planning on particular (important) commodities that flow through the port as proposed in Whitman et al. (2015). The emphasis on dock-specific investments is important because each dock has special equipment that handles particular commodities, each of which have different monetary values and are used as inputs to production by different industries. We treat different plans for preparedness resource allocation as discrete alternatives, and we make use of a multicriteria decision analysis technique, TOPSIS, or the technique of order preference similarity to the ideal solution, to compare these alternatives with industry impacts representing the multiple criteria weighted by their importance to decision makers. Moreover, an in-depth investigation of the impact of mitigation strategies on the dynamic inoperability per commodity provides a more holistic understanding of the proposed framework. We then compare the rankings with previous results in Whitman et al. (2015) to understand the impact of different historical freight profiles flowing through the port. The following section provides the methodological background of the interdependency modeling methodology, the decision analysis technique, and the integrated approach for dock resource allocation (extending some initial results by Whitman et al. 2015). The next section details a case study of a disruption of the inland waterway Port of Catoosa in Oklahoma, and the last section provides concluding remarks.

Methodological background

This section provides a discussion of the components of port preparedness decision framework: (i) the multi-industry impact model, (ii) the multicriteria decision analysis technique, and (iii) the approach for dock resource allocation used to evaluate different investment strategies for port preparedness.

Interdependency Model

The input–output model is a widely accepted Nobel Prize–winning model to linearly describe the interconnected relationships of industries (Leontief 1966). The basic input–output model is shown in Equation (1). Vector $\mathbf{x}$ of size $n \times 1$ corresponds to the total production outputs of n industries. Matrix $\mathbf{A}$ of size $n \times n$ corresponds to the proportional interdependence between industries, so $\mathbf{Ax}$ is the actual intermediate demand between industries resulting from producing $\mathbf{x}$. Finally, $\mathbf{c}$ provides final consumer demand. The U.S. Bureau of Economic Analysis (BEA) (2012a) provides extensive input–output data at different levels of industry aggregation, and other organizations exist in other countries to assemble similar commodity flow analyses. Readily available data make the input–output enterprise a practical approach for measuring economic interdependencies, despite the rigid linear relationship assumed by the model (Santos 2006). The economic impacts of disruptive events are well studied (Hallegatte 2008, 2013; Jonkeren and Giannopoulos 2014; Okuyama 2004; Rose 2009).

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

The input–output model was extended to provide a complementary perspective of inoperability, or the proportional reduction in functionality due to a disruptive event (Santos and Haimes 2004). The inoperability input–output model (IIM) is shown in Equation (2). Inoperability in infrastructure sector (e.g., transport) and industry sectors (e.g., manufacturing) i, q_i, takes on values ranging from 0 to 1, where a value of 0 indicates operation at an as-planned level and a value of 1 suggests completely halted functionality. Vector $\mathbf{q}$ represents *inoperability*, the proportional extent to which a sector is not productive (unrealized functionality), at time t. $\mathbf{c}^\star$ quantifies disruptions in demands as the normalized difference in as-planned production and perturbed demand. Matrix $\mathbf{A}^\star$ is a normalized interdependency matrix describing the degree of interdependence among sectors. Further details on the calculation of these parameters are found in Santos and Haimes (2004).

$$\mathbf{q} = \mathbf{A}^\star\mathbf{q} + \mathbf{c}^\star \Rightarrow \mathbf{q} = [\mathbf{I} - \mathbf{A}^\star]^{-1}\mathbf{c}^\star. \tag{2}$$

To model the dynamic nature of the onset of inoperability and subsequent recovery, Lian and Haimes (2006) introduced the dynamic IIM (DIIM), as shown in Equation (3). With a matrix $\mathbf{K}$, the DIIM models how the inoperability vector, $\mathbf{q}(t)$, as well as the vector of proportional demand reduction, $\mathbf{c}^\star(t)$, changes over time as the system recovers from a disruptive event.

$$\mathbf{q}(\boldsymbol{t}+1) = [\mathbf{I} - \mathbf{K}]\mathbf{q}(\boldsymbol{t}) + \mathbf{K}\left[\mathbf{A}^\star\mathbf{q}(\boldsymbol{t}) + \mathbf{c}^\star(\boldsymbol{t})\right]. \tag{3}$$

To calculate matrix $\mathbf{K}$, diagonal element k_i is calculated with a static recovery rate in Equation (4). Value $q_i(0)$ is the initial inoperability experienced in infrastructure or industry i following a disruptive event; $q_i(T_i)$ is the desired inoperability state after recovery, which requires T_i time periods to achieve ($q_i(T_i)$ can be small but nonzero); and $a^\star_{ii}$ is the ith diagonal element of the $\mathbf{A}^\star$ matrix.

$$k_i = \frac{\ln\left[\frac{q_i(0)}{q_i(T_i)}\right]}{T_i(1 - a^\star_{\mathrm{ii}})}. \tag{4}$$

Measures of interdependent performance after a disruptive event include (i) $q_i(t)$, the inoperability of infrastructure or industry i at a particular point in time (e.g., some number of days after a disruptive event); (ii) Q_i, the interdependent economic losses experienced in infrastructure or industry i calculated across a given time horizon, τ, calculated as $Q_i = \sum_{t=1}^{\tau} x_i q_i(t)$; and (iii) Q, a cumulative economic measure of the effect of inoperability across a given time horizon and across all infrastructures or industries, calculated as $Q = \sum_{i=1}^{n} \sum_{t=1}^{\tau} x_i q_i(t)$.

The IIM and its extensions have been applied to decision-making contexts across many disruptive event domains, including the aforementioned inland waterway disruptions (Baroud et al. 2014; MacKenzie, Barker, and Grant 2012; Pant et al. 2011, 2015), inventory policies (Barker and Santos 2010a, 2010b; Galbusera et al. 2014; MacKenzie, Santos, and Barker 2012), and electric power outages (Anderson et al. 2007; Li et al. 2018; MacKenzie and Barker 2012), among others.

Multicriteria Decision Analysis

Note that Q, the multi-industry economic impact measure discussed previously, sums economic losses in an unweighted fashion. However, to compare port preparedness investments strategies, we desire a new measure of interdependent impact that emphasizes inoperability and economic losses to particular industries that are important to the regional economy. As such, we make use of TOPSIS. TOPSIS is based on the philosophy of a compromise solution, providing a ranking of alternatives according to their shortest distance from the best alternative for a particular criterion and the farthest distance from the worst alternative for that criterion (Tzeng and Huang 2011).

Consider m alternatives, $j = 1, \ldots, m$, which are compared across n criteria, $i = 1, \ldots, n$. The performance of each alternative with respect to each criterion is contained in matrix $\mathbf{Y} = (y_{ij})$, where y_{ij} is the value of the ith criterion for alternative j. In this work, the alternatives represent the m preparedness strategies that allocate resources to different docks (discussed in the Illustrative Example section), and the decision criteria represent impact measures for each of n industries. For example, y_{ij} could represent economic loss for industry i, Q_i, calculated for a disruption after the implementation of preparedness strategy j. The weighting factor, w_i, is typically determined by the decision maker to assign importance to criterion i (this application uses a more objective regional economic importance weight, as discussed in the Illustrative Example section). The selection of criteria weights has a significant impact on the final solution and should be determined by the decision maker with domain experience (Olson 2004).

Performance ratings y_{ij} can be normalized if the various performance criteria exhibit different ranges (e.g., inoperability on [0, 1] along with economic losses in millions of dollars) with a variety of normalization approaches. The distributive normalization, shown in Equation (5), has been demonstrated to have most consistent qualities (Chakraborty and Yeh 2009).

$$r_{\mathrm{ij}} = \frac{y_{\mathrm{ij}}}{\sqrt{\sum_{j=1}^{m} y_{\mathrm{ij}}^2}}. \quad (5)$$

Once the performance ratings are normalized, a weighted normalized rating is calculated as shown in Equation (6):

$$v_{ij} = w_i r_{ij} \tag{6}$$

The positive ideal solution has all of the best attainable criteria values for a given alternative, whereas the negative ideal solution has all worst possible criteria values. The positive ideal solution, B^+, is found with Equation (7). Set C^+ represents the set of benefit criteria, where larger values of the criteria are preferred (e.g., profit, time between failure). Set C^- is the set of cost criteria, where smaller values of the criteria are preferred (e.g., inoperability, economic losses). Both benefit and cost criteria are discussed here for completeness, but the decision problem illustrated in the Illustrative Example section deals exclusively with cost criteria. Equation (7) suggests that the positive ideal solution consists of those weighted performance ratings that maximize benefit criteria and minimize cost criteria. Likewise, the negative ideal solution, or the weighted performance ratings that represent the smallest from set C^+ and largest from set C^-, is provided in Equation (8).

$$B^+ = \left\{v_1^+, \ldots, v_n^+\right\} = \left\{\left(\max_j v_{ij} | i \in C^+\right), \left(\min_j v_{ij} | i \in C^-\right)\right\} \tag{7}$$

$$B^- = \left\{v_1^-, \ldots, v_m^-\right\} = \left\{\left(\min_j v_{ij} | i \in C^+\right), \left(\max_j v_{ij} | i \in C^-\right)\right\}. \tag{8}$$

Once the positive ideal, B^+, and negative ideal, B^-, solutions are determined for each performance criterion, the Euclidean distance from the positive and negative ideal solutions is calculated for each alternative as shown in Equations (9) and (10):

$$d_j^+ = \sqrt{\sum_i \left(v_i^+ - v_{ij}\right)^2} \tag{9}$$

$$d_j^- = \sqrt{\sum_i \left(v_i^- - v_{ij}\right)^2}. \tag{10}$$

The preference order of alternatives can then be generated by ordering the measure in Equation (11) in descending order where D_j is a measure of the similarity to the positive ideal solution (scores closer to 1 suggest closeness to the positive ideal solution):

$$D_j = \frac{d_j^-}{d_j^+ - d_j^-}. \tag{11}$$

One major assumption of TOPSIS is the independence of criteria, which might not be realistic when considering the specific problem addressed in this work. Because the interdependencies have been modeled with the input–output model described earlier in this section, TOPSIS might overevaluate correlated performance criteria that are highly interdependent. For a small number of performance criteria, there are several techniques to address correlated criteria, such as modifying the distance formula used in Equations (9) and (10) or modifying the TOPSIS method itself (Bondor and Muresan 2012; C. H. Chang et al. 2010; Vega et al. 2014). Due to the low number of alternatives m relative to the number of performance criteria n for the specific application in this article, there are not enough samples (alternatives) to sufficiently estimate the correlation between performance criteria, which are thus assumed to be independent.

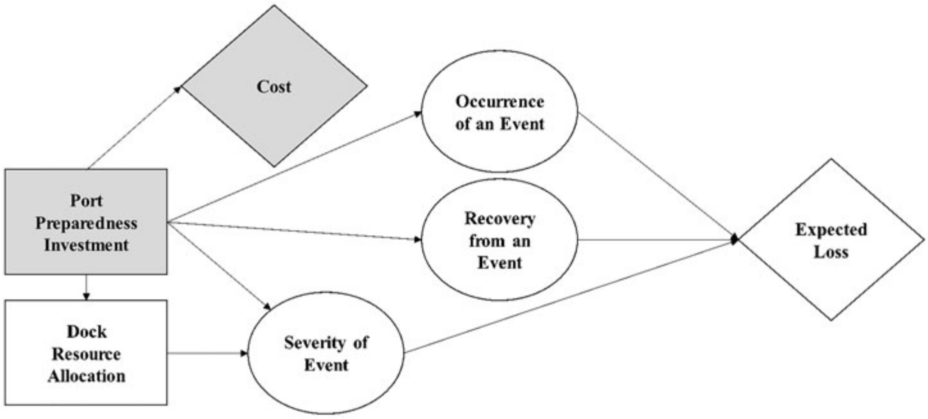

Figure 1. Influence diagram describing the infrastructure preparedness investment decision-making process.

TOPSIS is just one of several techniques for comparing discrete alternatives under multiple criteria. We choose TOPSIS due to its simplicity and its ability to implement a compromise solution. The choice of decision analysis technique could influence the ranking of alternatives (Opricovic and Tzeng 2004), though a comparison is not sought here.

Dock Resource Allocation Approach

To relate port preparedness strategies to resulting inoperability and economic losses, the simulation used by Baroud et al. (2014) is modified to reflect dock-specific commodity flows described in Pant et al. (2015). The relationship between the investment and resulting preparedness of the port is shown in Figure 1 in an influence diagram adapted from Baroud et al. (2014). From the figure, the amount to invest in the entire port is assumed to be already determined and is shaded in grey. The cost objective, represented by a diamond, is the entire amount invested in the port and is not a decision point in the article but does influence other parameters. The decision to make—how much to invest in each dock—is represented by a rectangle and will vary by dock for each strategy. Both the total amount invested in the port and the amount invested in each dock indirectly impact the objective function, which is the expected economic loss per industry. The total amount invested in the port affects three uncertainties: (i) the probability of a disruptive event occurring, (ii) the recovery time for the port after a disruptive event has occurred, and (iii) the severity of the disruption. The amount invested will directly impact the probability of occurrence of a disruption and the severity through a relationship between a factor of influence of the investment and the parameters of the probability distribution describing these events. The recovery time is indirectly influenced through the initial impact on industries. The amount invested in each dock also impacts the extent of damage suffered by each of the industries flowing through the dock with an additional level of protection for the commodities flowing through the port. Port-wide disruptions from large-scale events can be short term in nature (e.g., an accident) or long term (e.g., flooding) and impact the entire port and each dock differently.

The resource allocation among docks results in a different level of preparedness for each dock and thus a different level of severity of the effect of a disruptive event. This level of preparedness is modeled with a factor of influence θ_i to reflect the level of influence of an investment by dock, linearly related to the dock investment amount, I_i, and the maximum amount to be invested, $I_{\max}$, as shown in Equation (12):

$$\theta_i = \frac{I_i}{I_{\max}}. \tag{12}$$

The factor θ_i takes on a value between 0 and 1 with larger values corresponding to a higher level of preparedness. The value $I_{\max}$ is much larger than the total port investment to reflect the likelihood that the amount invested in the port is not the maximum amount of protection achievable. These dock-specific investments influence the uncertainty associated with the severity of a disruptive event and are the direct connection between the amount invested and the impact those investments have on port preparedness. According to Baroud et al. (2014), the probability that a disruption occurs is equal to 0.02, and it is assumed to decrease exponentially with increasing investment. The severity of the disruption is defined for each individual dock based on the factor of influence, θ_i. The severity of the disruption affects the sample mean of the demand perturbation as described by Baroud et al. (2014) for each commodity flowing through the dock. Docks that have a higher investment amount allocated will suffer less of a demand perturbation.

The output of this simulation is in the form of a distribution of expected losses EQ_i per industry i. The expected value of the distribution of expected losses for each industry is used as criterion i in TOPSIS. To capture the potentially extreme nature of industry impacts, two conditional upper tail values were also considered: the average of the largest 5% of industry losses ($CEQ_{i,0.05}$) and of the largest 1% of industry losses ($CEQ_{i,0.01}$) (Baroud et al. 2014; Haimes 2009).

The proposed resource allocation approach assumes that the level of preparedness of each dock relies on the investment level, as well as the amount and type of commodities flowing through the dock. Other structural and operational dock characteristics would normally be explicitly considered in the assessment of the dock preparedness level. The approach adopted here is general and assumes that the investment can be used to enhance any dock characteristic, such as improving security infrastructure, access controls, inspection systems, law enforcement agency collaborations, lighting, and personnel training, among others (Pate et al. 2007).

Illustrative example: inland waterway port

The framework developed in this article is illustrated with a case study of an inland waterway port disruption at the Port of Catoosa, an inland waterway port in Tulsa, Oklahoma, along the Mississippi River Navigation System. Four different docks make up the port, each equipped to handle different specific commodities. The dry cargo dock handles large items, primarily steel, iron, and machinery. The dry bulk dock handles a variety of loose commodities that are moved by conveyer, such as sand, gravel, and fertilizer. The grains dock moves agricultural products such as corn, wheat, and soybeans. The liquid bulk dock moves liquid products including chemicals, liquid fertilizers, and even molasses.

The Port of Catoosa applied to the DHS PSGP for funding in 2012 and was awarded $380,000 to strengthen the port's security against disruptive events (DHS 2012). Though administrators of the Port of Catoosa likely put together a specific application to receive those funds, a broader set of preparedness plans could have been developed with that funding amount, dividing resources to the four docks. Discrete investment alternatives provide a different level of preparedness for each dock, resulting in a different reduction in inoperability and economic impact for each industry that relies on the port's commodities if the dock is disrupted. This economic impact is distributed among all industries that are affected by the disruption, but decision makers at the Port may want to prioritize industries according to their criticality to the Oklahoma economy when deciding where to target their funding.

Assumptions

The input data used to investigate this case study can be divided into two categories: simulation input and decision analysis input. To simulate the annual flow of commodities through the Port of Catoosa, tonnage values through the individual dock were derived from the U.S. Army Corps of Engineers and adapted to an economic value amount from commodity flow surveys (Margreta et al. 2014; U.S. Army Corps of Engineers 2011). Data from the 2012 benchmark data set from the Bureau of Economic

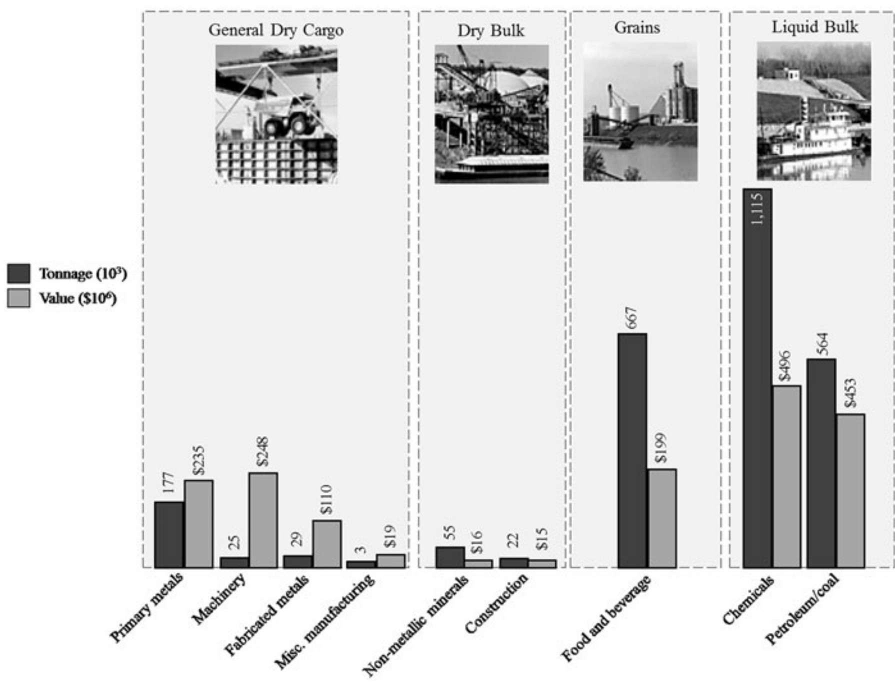

Figure 2. Estimates of the 2012 annual commerce through specific docks at the Port of Catoosa, shown in value ($\$10^6$) and tonnage ($10^3$).

Table 1. Estimates of the 2012 annual commerce through specific docks by value at the Port of Catoosa, in $\$10^6$ for imports, exports, and total value.

Dock name	Description	NAICS industry	Import value	Export value	Total value
General dry	Primary metals	331	230	5	235
Cargo	Fabricated metal products	332	96	14	110
	Machinery	333	0	248	248
	Miscellaneous manufacturing	339	0	19	19
Dry bulk	Nonmetallic mineral products	327	7	8	16
	Construction	23	15	0	15
Grains	Food and beverage products	311FT	16	183	199
Liquid bulk	Chemical products	325	255	241	496
	Petroleum and coal products	324	26	427	453

Table 2. Resource allocation investment strategies, including dock-specific allocation (in $\$10^3$).

	Dock				
Strategy	General dry cargo	Dry bulk	Grains	Liquid bulk	Description
S1	380	0	0	0	Prioritize general dry cargo dock
S2	0	380	0	0	Prioritize dry bulk dock
S3	0	0	380	0	Prioritize grains dock
S4	0	0	0	380	Prioritize liquid bulk dock
S5	95	95	95	95	Divide evenly among docks
S6	8	8	133	232	Percentage of tonnage, exports
S7	34	11	95	239	Percentage of tonnage, total
S8	95	4	61	220	Percentage of value, exports
S9	129	8	42	201	Percentage of value, total
S10	57	0	19	304	Combination of alternatives 4, 9

Analysis were used to calculate the $\mathbf{A}^{*}$ matrix (MacKenzie, Barker, and Grant 2012; Pant et al. 2011).

The estimated total annual value of imports and exports (measured in millions of U.S. dollars) through the Port of Catoosa through each dock in 2012 is shown in Figure 2. The bulk of the valuable freight appears to flow through the liquid bulk dock, with dry bulk dock commodities having little value. Even though the tonnage through the grains dock is high, the general dry cargo dock has more value with less tonnage. The nine industries shown in the figure are part of 62 BEA industry and infrastructure sectors making up this illustrative example. The complete list of 62 BEA industries is included in Table A1 (see Appendix). In addition, Table 1 provides the total tonnage and value of commodities moving through the Port of Catoosa in terms of imports and exports.

The nine dock-specific industries, as labeled by the North American Industry Classification System (NAICS), that flow through the four docks include primary metals, machinery, fabricated metal products, miscellaneous manufacturing, nonmetallic mineral products, construction, food and beverage products, chemical products, and petroleum and coal products. Each dock is equipped with specific machinery to handle the types of commodities associated with it. Preparedness plans allocate resources to each dock, resulting in different abilities to withstand and recover from disruptive events and maintain flows of dock-specific commodities.

Ten resource allocation strategies were developed, as shown in Table 2. The maximum amount of funding distributed to a dock is \$380,000, which corresponds to the total budget for resource allocation across the port. For example, strategy S7 allocates

Table 3. 2012 Top 10 subset of 62 BEA industry sectors in Oklahoma (state GDP in $\$10^9$).

Industry	NAICS industry	State GDP	Percentage of total
Oil and gas extraction	211	20.5	12
State and local government	GSL	19.0	11
Real estate	531	13.7	8
Retail trade	44RT	10.4	6
Wholesale trade	42	9.7	6
Federal government	GF	8.0	5
Construction	23	7.0	4
Ambulatory health care services	621	5.6	3
Administrative and support services	561	5.1	3
Hospitals and nursing and residential care facilities	622HO	5.0	3

resources based on the percentage of total commodity flow through each dock measured in tonnage (thereby investing most in the liquid bulk dock). These investment strategies will be used to calculate a distribution of expected losses per industry i through 10,000 simulation iterations.

The 10 most important industries to the Oklahoma economy, as determined by state gross domestic product (GDP) measured in billions of U.S. dollars, are shown in Table 3 (BEA 2012b). The percentage of total state GDP is shown in the fourth column, which determines the weight, w_i, for industry i as referenced in Equation (6). Oklahoma's total GDP is valued at \$175 billion with the top 10 industries in Oklahoma representing 60% of overall state GDP. The respective percentages of total state GDP per industry i for all 62 industries are calculated to parameterize w_i for each industry i. We prioritize the industries that contribute the most to Oklahoma's economy and weight all 62 BEA industries by Oklahoma's state GDP. None of the commodities flowing through the Port of Catoosa are in the top 10 industries of Oklahoma except for construction (dry bulk dock), but they might be strongly related. For example, oil and gas extraction is the most profitable industry in Oklahoma and has a strong interdependency with the petroleum products industry that flows through the liquid bulk dock at the Port of Catoosa. By prioritizing important Oklahoma industries, we achieve a holistic perspective and the best alternative might not be an obvious decision when considering economic losses alone.

To account for the uncertainty in the severity of disruptions described in the influence diagram in Figure 1, Monte Carlo simulation is used to simulate multiple disruption scenarios and the effectiveness of each of the 10 resource allocation strategies described in Table 2. The following steps guide the simulation for each iteration and for each investment strategy (modified from Baroud et al. [2014] to allow for dock-specific investments):

1. Based on the current resource allocation strategy, calculate the factor of influence for each dock.
2. Generate a random variable from the power law distribution within the bounds of minimum and maximum severity (minimum of 10 days, maximum of 100 days).
3. Given the severity of disruption, dock-specific factor of influence, and elicited values for $\mathbf{c}^*_{\max}$ and $\mathbf{q}_{\max}(0)$, calculate sample mean, $\overline{\mathbf{X}}$, and standard deviation, s, of the demand perturbation.
4. Calculate the parameters of DIIM, which include $\mathbf{q}(0)$ and recovery matrix $\mathbf{K}$ (both impacted by dock-specific factor of influence).

5. Using sample mean, $\overline{\mathbf{X}}$, and standard deviation, s, from step 3, compute estimates for beta distribution which describes demand perturbation. Draw random elements from this distribution for each industry element in the demand perturbation vector.
6. Compute inoperability vector at each point in time.
7. Compute expected value of industry-specific total economic loss as the product of loss and probability p of a disruptive event, $\mathbf{EQ}(T) = \mathbf{Q}(T)p$.

The above steps are repeated for 10,000 iterations and for each investment strategy results in an industry-specific cost distribution EQ per strategy. The mean values and conditional means for industry-specific total economic losses are used in TOPSIS to rank resource allocation strategies based on shareholder specific weighting criteria.

Results

The economic losses experienced in each sector are due to a wide range of factors related to demand perturbation and production inoperability. These factors can be endogenous (e.g., the disruption of port or dock operations) or exogenous (e.g., the cost and availability of alternative supply sources and modes of transportation). The probability distribution governing the disruption severity and demand perturbation is a theoretical representation of the different factors resulting in economic losses for each industry.

To visualize the impact of the investment on total expected losses, a sample distribution of expected losses when no investment is made and for strategy 1 is shown in Figure 3a. The expected economic loss for all sectors was calculated by running 10,000 simulations of the probability distribution of severity under two preparedness strategies: (i) no preparedness investment and (ii) S1, where all resources are invested in the dry bulk dock. Figure 3a is a histogram of the frequency of expected economic losses for these 10,000 simulations under each of the respective strategies. The colored dashed vertical lines represent the mean and conditional means of each respective distribution. As shown in Figure 3a, the port investment for strategy 1 has a large impact on the total expected losses relative to no investment at all. Figure 3b alternatively plots sample distributions of total economic losses for strategy 3 and strategy 10. As shown in the figure, the distributions look similar with expected values and conditional means much

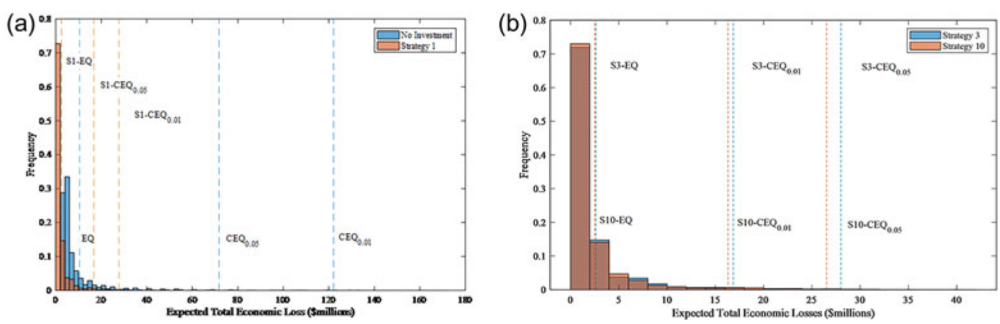

Figure 3. Normalized frequency of the expected total economic losses across all industries comparison for certain scenarios for 10,000 simulations. (a) No investment (blue) and strategy 1 (orange) and (b) Strategy 3 (blue) and strategy 10 (orange).

Table 4. Recorded *p*-values from KS test comparing simulation results of total expected economic losses distributions of each strategies.

Strategy	1	2	3	4	5	6	7	8	9	10
1	1	1.2E-101	5.8E-122	2.9E-155	3.7E-128	6.3E-156	5.0E-151	1.0E-142	2.4E-151	2.6E-141
2	1.2E-101	1	1.6E-126	3.8E-153	1.6E-113	2.2E-150	1.1E-146	5.8E-139	8.3E-148	6.7E-140
3	5.8E-122	1.6E-126	1	4.2E-171	8.0E-144	4.6E-170	2.9E-163	1.3E-155	1.9E-165	1.7E-152
4	2.9E-155	3.8E-153	4.2E-171	1	6.3E-149	8.8E-119	4.6E-132	5.8E-139	4.2E-130	2.8E-123
5	3.7E-128	1.6E-113	8.0E-144	6.3E-149	1	7.0E-143	4.7E-140	1.4E-133	3.8E-141	8.5E-137
6	6.3E-156	2.2E-150	4.6E-170	8.8E-119	7.0E-143	1	6.1E-87	1.7E-71	2.4E-82	8.4E-106
7	5.0E-151	1.1E-146	2.9E-163	4.6E-132	4.7E-140	6.1E-87	1	1.6E-96	2.6E-102	8.9E-117
8	1.0E-142	5.8E-139	1.3E-155	5.8E-139	1.4E-133	1.7E-71	1.6E-96	1	1.5E-89	1.9E-124
9	2.4E-151	8.3E-148	1.9E-165	4.2E-130	3.8E-141	2.4E-82	2.6E-102	1.5E-89	1	3.3E-118
10	2.6E-141	6.7E-140	1.7E-152	2.8E-123	8.5E-137	8.4E-106	8.9E-117	1.9E-124	3.3E-118	1

closer together than those shown in Figure 3a. In order to determine whether the sample distributions of total economic losses obtained from Monte Carlo simulation are statistically different, a pairwise comparison of the 10 distributions was done using a two-sample Kolmogorov-Smirnov (KS) test. Also known more generally as the Smirnov test, the KS test quantifies the distance between empirical distributions and is one of the most useful and general nonparametric method for comparing two distributions (Berger and Zhou 2005). Despite the similarity in distributions, results from the KS statistic report *p*-values less than a significance level of $\alpha = 0.001$ and are shown in Table 4. Thus, all 10 sample distributions of total expected economic losses obtained from the 10 decision alternatives are statistically different from each other. The distributions for the other strategy types are similar in behavior in that all have lower mean and conditional means compared to no investment. Each run simulates a disruption scenario, and the overall impacts are multiplied by the probability of the disruption occurring. The severity of a disruptive event is modeled with the power law distribution. Extreme events of low likelihood but high consequence that might be of particular interest to decision makers are effectively modeled with a power law distribution (Clauset et al. 2007; Johnson et al. 2006). Baroud et al. (2014) considered expected value and upper tail values of total economic losses across all industries, EQ. The mean total expected losses, as well as the conditional means associated with the top 1% ($CEQ_{0.01}$) and top 5% ($CEQ_{0.05}$) values, are plotted on the horizontal axis in dashed lines to visualize what information decision makers might extract from this distribution.

To visualize the impact of dock-specific investments, the mean demand disruption for two resource allocation strategies is shown in Figure 4. Each dock-specific investment mitigates the severity of the disruption for all industries whose commodities flow through the dock. The mean disruption per industry with no resources allocated is shown in the figure for comparison as a base case scenario. The "no investment" scenario results in the largest disrupted demand, because there were no resources allocated toward preparedness. For strategy S3, all resources were allocated to the grains dock, primarily measured in terms of food and beverage products (industry 311FT) along the horizontal axis of Figure 4. For strategy S10, most of the resources were concentrated on the liquid bulk dock (chemicals and coal/petroleum) and had a much larger impact on mitigating the amount of demand that was disrupted when compared to strategy S3. It is clear from Figure 4 that although strategy S3 greatly reduced the demand disrupted for the grains dock, strategy S10 is much more effective at mitigating disrupted demand across more industries with the highest value.

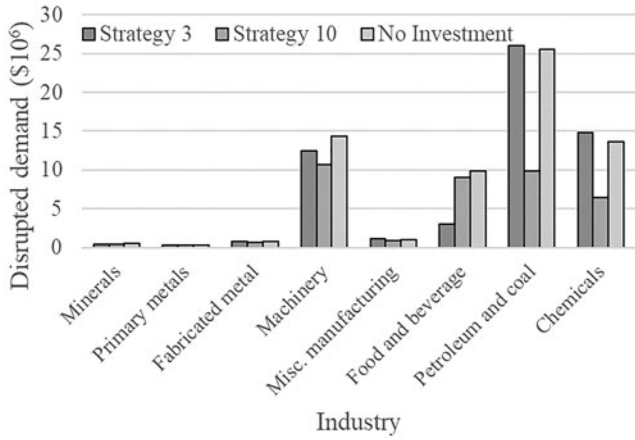

Figure 4. Comparison of strategies 3 and 10 on effectiveness of reducing the average amount of demand disrupted. Each graph shows average demand disruption with no investment for comparison.

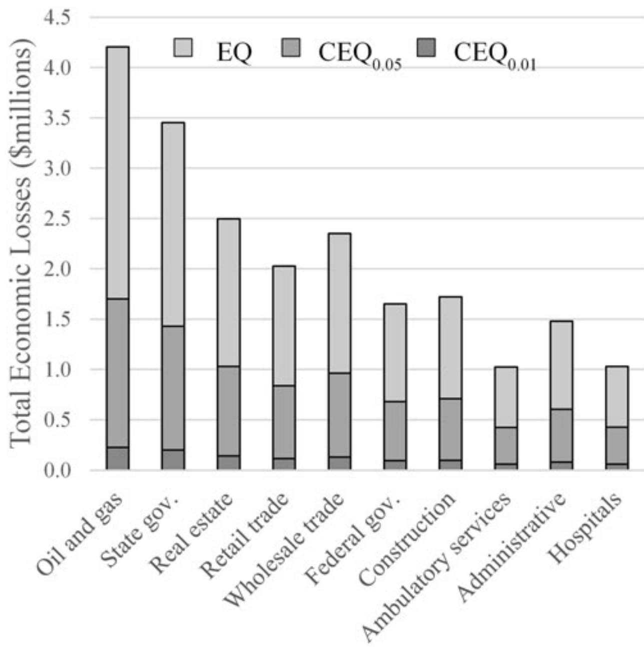

Figure 5. Mean and conditional mean (top 1% and 5%) economic loss for each of the top 10 industries in Oklahoma by state GDP.

Another perspective of the impact of disruptions is to visualize the total economic loss by industry of the top 10 industries in Oklahoma by state GDP. In addition to the mean expected loss, extreme values are considered. Figure 5 shows the mean and extreme values for the top industries in Oklahoma under strategy S10. Even though only strategy S10 is shown, the behavior is consistent across most strategies. As shown in Figure 5, the average expected loss for all 10 of the top industries is well under $500,000, but the conditional means vary greatly and have large ranges (e.g., oil and gas industry). Considering only average expected losses does not fully capture the extreme

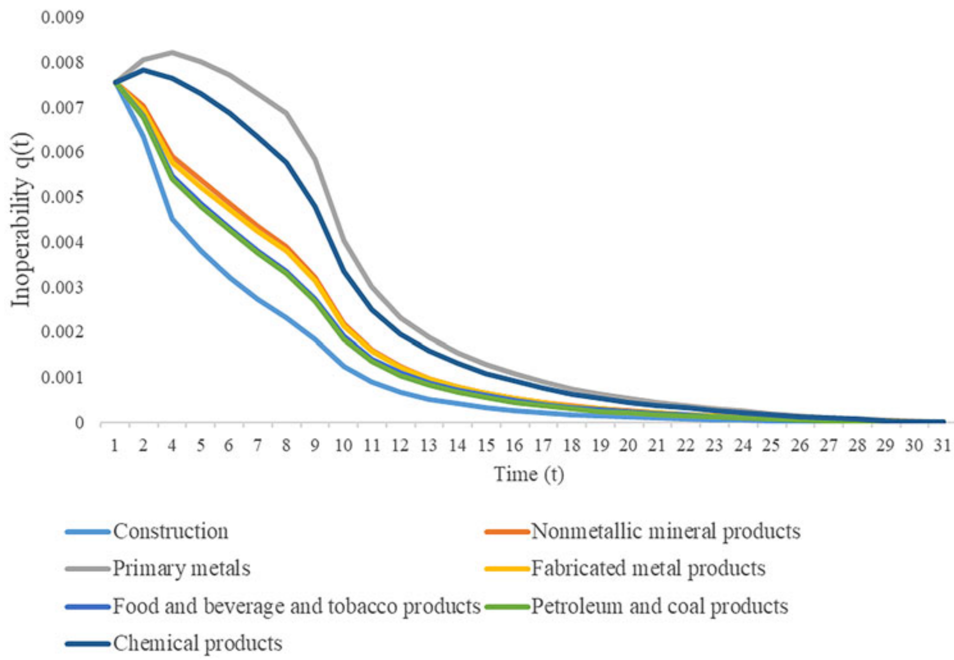

Figure 6. Inoperability, $q_i(t)$, over time (t) in days for each industry with no resources allocated.

industry-specific impacts, and this does not fully describe the actual loss if this disruption occurred because the expected loss includes the low probability of occurrence.

From the Interdependence Model subsection, inoperability changes over time as each industry recovers from the port disruption. Figure 6 shows the recovery of each of the seven commodities imported through the Port of Catoosa and how each industry recovers differently over time when no resources are allocated. Shown in Figure 6, all industries start from the same inoperability point but vary due to industry type, with primary metals and chemical products having higher peaks relative to the other imports. These two industries are the top two imports (in value) through the Port of Catoosa and have slower recovery relative to the other industries. Inoperability appears to impact commodities differently depending on whether they are the imports or exports, and this could reflect the varied propagation of inoperability across interdependent systems.

To visualize the effectiveness of preparedness strategies, the industry inoperability resulting from each import commodity perturbation is analyzed per strategy in Figures 7a–7g. The biggest difference between resource allocation strategies is their effect on the initial inoperability experienced by each industry and the time until full recovery where the inoperability is approximately 0. As shown in each of the graphs in Figure 7, each strategy affects each industry differently. For example, in Figure 7a, the effect of inoperability in the construction industry for each of the 10 strategies is consistent, with S2 and S4 having relatively little effect on the initial inoperability compared to the other strategies. When compared to Figure 6, all seven industries have a lower initial inoperability regardless of the strategy used. This is due to the port-wide investment impact on the severity of the event as discussed with Figure 1, but the impact of the individual strategies is apparent. For example, in Figure 7f, the petroleum and coal industry is

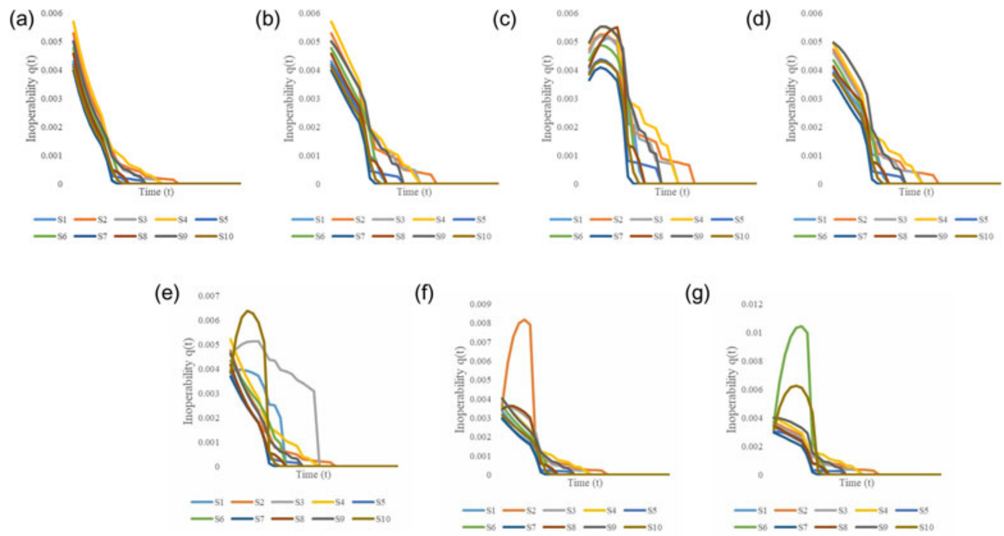

Figure 7. Inoperability, $q_i(t)$, over time in each industry for each preparedness strategy: (a) construction, (b) nonmetallic minerals, (c) primary metals, (d) fabricated metals, (e) food and beverage, (f) petroleum and coal, and (g) chemical products.

Table 5. Ranking of resource allocation strategies using (i) the typical unweighted economic loss measure and (ii) TOPSIS to account for the weighted compromise solution.

	Unweighted economic loss			Weighted economic loss		
Rank	EQ	$CEQ_{0.05}$	$CEQ_{0.01}$	EQ	$CEQ_{0.05}$	$CEQ_{0.01}$
1	S10	S10	S10	S4	S10	S10
2	S4	S4	S4	S10	S4	S4
3	S6	S1	S7	S6	S2	S7
4	S9	S6	S6	S2	S6	S8
5	S8	S8	S8	S8	S8	S6
6	S5	S5	S5	S7	S7	S2
7	S7	S2	S1	S9	S1	S5
8	S2	S7	S2	S5	S9	S9
9	S1	S9	S9	S1	S5	S1
10	S3	S3	S3	S3	S3	S3

analyzed for all 10 strategies, with strategy S2 having a negative impact on the inoperability with a swift rise in inoperability before decreasing to 0. Recall that strategy S2 invests all resources in the dry bulk dock with no resources allocated to the liquid bulk dock, which explains this negative effect on the petroleum and coal industry. When comparing all seven industries, the industries with the higher imports, such as primary metals and chemical products, have more extreme behaviors across strategies, which indicates that imports are more sensitive to inoperability propagation than exports.

Table 5 lists the strategies according to their ranking based on the economic loss measure, such that the strategy that ranks first results in the lowest economic loss. Expected and conditional expected values provide three measures for the economic loss, EQ, $CEQ_{0.05}$, and $CEQ_{0.01}$. The three measures are calculated for two cases, yielding (i) unweighted economic losses without using TOPSIS and (ii) weighted economic losses informed by several criteria.

The first three columns of Table 5 represent expected and conditional expected losses summed across industries without using TOPSIS (that is, without considering the importance of industries and without accounting for the compromise solution). The expected and conditional expected losses provide different perspectives on which strategies effectively reduce typical and worst-case losses, and the rankings of strategies differ depending on the metric being used.

Alternatively, columns 4–6 in Table 5 represent results from TOPSIS, where *EQ*, $CEQ_{0.05}$, and $CEQ_{0.01}$ columns represent the TOPSIS results calculated from the expected and conditional expected values, respectively. When only focusing on economic loss, the suggested strategies target the liquid bulk and general dry cargo docks, which is not surprising because they are shipping the most valuable goods. The low ranking of strategy 9 is surprising because allocating funds by the respective value of goods flowing through the port was initially considered a logical decision; however, the interdependent impacts and stakeholder interests lower the importance of the value of individual goods. However, when state GDP is incorporated as a weighting criterion in TOPSIS, investment strategies that emphasize the dry bulk rise significantly in ranking though they are not identified by TOPSIS as the most ideal. This is logical because construction industry goods are shipped through the dry bulk dock, and this industry is important to Oklahoma's economy. In addition, depending on the risk aversion of the decision maker, different strategies are more appealing and yield less extreme losses when compared to other strategies. Even with more emphasis on the construction commodities moving through the dry bulk dock, the top rankings do not vary greatly across perspectives due to the dominance of liquid bulk cargo. When compared to the rankings from the 2007 analysis of the same alternatives (Whitman et al. 2015), the rankings are consistent in identifying strategy S10 in the upper ranks but have more variability than is shown in Table 4. This is most likely due to the freight profiles through the Port of Catoosa varying greatly between 2007 and 2012, with more commodities shipped through the liquid bulk dock in 2012 than was seen in 2007.

Validation and verification processes are critical to assess the robustness of the results. The outcome of the analysis has been validated using results from a prior study performed with economic data from 2007 (Whitman et al. 2015). Both analyses (i) identify S10 to be among the highest ranking strategies and (ii) suggest that the remaining strategies exhibit more variability, which is attributed to the differences in the freight profiles.

Concluding remarks

One focus of risk-based preparedness planning is the resilience of vulnerable infrastructure systems. An ability to measure interdependent system impacts helps decision makers understand the effect that investment strategies have on mitigating risk. This article builds upon previous work by Pant et al. (2015) and Baroud et al. (2014) by combining dock-specific impacts with measuring investment efficacy on mitigating risk. A multicriteria decision analysis tool, TOPSIS, is incorporated to enable the decision maker to prioritize industries relevant to the local economy (or some other weighting scheme), balance tradeoffs associated with risk aversion, and understand system-level impacts of their preparedness planning decisions. This article provides valuable information because it considers that an "optimal" allocation of resources might not be feasible, thereby enabling a ranking of discrete investment strategies. In addition, by evaluating discrete decision alternatives, instead of providing simply the optimal investment, decision makers have a practical tool to help them select from competing bids and input their own stakeholder criteria. Doing so will allow decision makers to allocate resources effectively, producing a compromise solution that accounts for multiple industries.

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Appendix

Table A1. 62 BEA industries and associated NAICS code and description.

Industry	Code	Description
1	111CA	Farms
2	113FF	Forestry, fishing, and related activities
3	211	Oil and gas extraction
4	212	Mining, except oil and gas
5	213	Support activities for mining
6	22	Utilities
7	23	Construction
8	321	Wood products
9	327	Nonmetallic mineral products
10	331	Primary metals
11	332	Fabricated metal products
12	333	Machinery
13	334	Computer and electronic products
14	335	Electrical equipment, appliances, and components
15	336	Motor vehicles, other transportation equipment
16	337	Furniture and related products
17	339	Miscellaneous manufacturing
18	311FT	Food and beverage and tobacco products
19	313TT	Textile mills and textile product mills

(*continued*)

Table A1. Continued.

Industry	Code	Description
20	315AL	Apparel and leather and allied products
21	322	Paper products
22	323	Printing and related support activities
23	324	Petroleum and coal products
24	325	Chemical products
25	326	Plastics and rubber products
26	42	Wholesale trade
27	44RT	Retail trade
28	481	Air transportation
29	482	Rail transportation
30	483	Water transportation
31	484	Truck transportation
32	485	Transit and ground passenger transportation
33	486	Pipeline transportation
34	487OS	Other transportation and support activities
35	493	Warehousing and storage
36	511	Publishing industries, except Internet (includes software)
37	512	Motion picture and sound recording industries
38	513	Broadcasting and telecommunications
39	514	Data processing, Internet publishing, and other information services
40	521CI	Federal Reserve banks, credit intermediation, and related activities
41	523	Securities, commodity contracts, and investments
42	524	Insurance carriers and related activities
43	525	Funds, trusts, and other financial vehicles
44	531	Real estate
45	532RL	Rental and leasing services and lessors of intangible assets
46	5411	Legal services
47	5415	Computer systems design and related services
48	5412OP	Miscellaneous professional, scientific, and technical services
49	55	Management of companies and enterprises
50	561	Administrative and support services
51	562	Waste management and remediation services
52	61	Educational services
53	621	Ambulatory health care services
54	622HO	Hospitals and nursing and residential care facilities
55	624	Social assistance
56	711AS	Performing arts, spectator sports, museums, and related activities
57	713	Amusements, gambling, and recreation industries
58	721	Accommodation
59	722	Food services and drinking places
60	81	Other services, except government
61	GF	Federal government
62	GSL	State and local government