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Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport

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In this paper, an indicator of network resilience is defined that quantifies the ability of an intermodal freight transport network to recover from disruptions due to natural or human-caused disaster. The indicator considers the network's inherent ability to cope with the negative consequences of disruptions as a result of its topological and operational attributes. Furthermore, the indicator explicitly accounts for the impact of potential recovery activities that might be taken in the immediate aftermath of the disruption to meet target operational service levels while adhering to a fixed budget. A stochastic mixed-integer program is proposed for quantifying network resilience and identifying an optimal postevent course of action (i.e., set of activities) to take. To solve this mathematical program, a technique that accounts for dependencies in random link attributes based on concepts of Benders decomposition, column generation, and Monte Carlo simulation is proposed. Experiments were conducted to illustrate the resilience concept and procedure for its measurement, and to assess the role of network topology in its magnitude.

Key words: resilience; reliability; vulnerability; flexibility; disaster management; intermodal freight transport
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1. Introduction

The rapid development of e-commerce, economic globalization, just-in-time production, and logistics and supply chain systems over past decades has lead to significant need for efficient and effective management of freight movements. Individuals and companies have become increasingly dependent on the freight transport system to deliver their goods. In fact, U.S. domestic freight moved by air, truck, and railroad increased by 28.5% between 1996 and 2007 (Bureau of Transportation Statistics 2010). Furthermore, domestic freight demand is projected to increase by approximately 65% and international trade is projected to double by 2035 as compared with 2010 (FHWA 2006). Consequently, significant increase in demand for freight transport in coming years is anticipated. However, the freight transport sector is operating at or near its capacity in many regions of the world, including the United States (AASHTO 2007). Despite this, in most industrialized nations there has been little increase in the capacity of the freight transport system. In fact, in the United States, between 1980 and 2007, the highway network expanded by under 5% whereas highway vehicle-miles traveled grew by 98%. Moreover, ton-miles of freight moved along the rail freight network doubled during this period at the same time that track-miles decreased by 23.5% (FHWA 2009). Simultaneously, risks from accidents, weather-induced hazards, and terrorist attack on the freight transport systems have dramatically increased. Thus, trucking companies, rail carriers, infrastructure managers, and terminal and port operators must invest in security measures to prevent or mitigate the effects of disasters resulting from such incidents. Even less-monumental incidents, such as derailment of cars from tangent track, can lead to network wide disruptions in service and ensuing delays. The Hatfield accident of 1993 in Great Britain provides evidence of this (Commission for Integrated Transport 2002). The demand for high-quality service at reasonable cost and with adequate protection from these various external forces has placed a heavy burden on the freight transport industry. There is increased pressure on this sector to balance these conflicting objectives of providing high service and security levels while simultaneously offering low-cost transport alternatives.

A characteristic of a secure and highly functioning transport network, i.e., a resilient network, is its ability to recover from disruptions. This ability depends on the network structure and activities that can be undertaken to preserve or restore service in the event of a disaster or other disruption. For example, Chrysler used expedited truck service to back up air freight transport for transporting critical components from Virginia to Mexico immediately after September 11, 2001 (Martha and Subbakrishna 2002). In this paper, an indicator of network resilience is defined that quantifies the ability of an intermodal freight transport network to withstand and quickly recover from a disruption. Recovery activities that might be taken in the immediate aftermath of a disruption, as well as the duration of time and investment required to undertake related actions, are considered a priori.

To quantify a network's level of resilience, a solution technique based on concepts of Benders decomposition, column generation, and Monte Carlo simulation is proposed. In addition to quantifying the network's level of resilience, this technique determines an optimal course of action (i.e., set of activities) to undertake in the immediate aftermath of a disaster given target operational levels and a fixed budget. Research has been conducted on steps that can be taken to quickly restore system performance following a disaster (e.g., Daryl 1998; Williams, Batho, and Russell 2000; and Juhl 1993 consider recovery actions in the aftermath of tornados, tropical storms, and bombings). Quick identification of the appropriate actions to take can play a crucial role in mitigating ensuing postdisaster economic and societal loss. For example, repair activities can be undertaken to restore critical infrastructure damaged in the disaster to predisaster conditions, traffic can be rerouted, equipment and personnel can be rescheduled, efficiencies in operations can be enhanced, and logistics providers can collaborate. That is, the performance of a network postdisaster depends not only on the inherent capability of the network to absorb externally induced changes but also on the actions that can be taken in the immediate aftermath of the disaster to restore system performance. The resilience indicator can aid in predisruption network vulnerability assessment and making predisaster, vulnerability-reduction investment decisions.

In the next section, related studies on the measurement of network performance under uncertainty are described. Network resilience is defined and a stochastic mixed-integer program based on an intermodal freight network representation is presented for computing resilience in §3. In §4, Monte Carlo simulation is proposed for generating possible network states for given problem scenarios with dependencies. Benders decomposition is employed in the exact solution for a given network state. Column generation is applied in solution of the Benders subproblems. The network resilience definition, solution technique, and resulting resilience levels, along with recovery activities, are illustrated on the Double-Stack Container Network (Morlok and Chang 2004; Sun, Turnquist, and Nozick 2006) under a variety of scenarios, including scenarios meant to replicate conditions under flooding, earthquake, and terrorist attacks, in §5. Results from additional experiments designed to uncover the role network structure plays in resilience level are also presented. The last section summarizes the contributions of this work and discusses future potential extensions.

2. Related Studies

Events that cause disruptions in nearly all human-made systems are often unpredictable, and, at some level, are inevitable. Thus, to prepare for such events, significant effort has been spent to predict system performance under disruption, identify critical functions and vulnerabilities, and develop means of reducing these vulnerabilities. Measures of network-level vulnerability have been employed widely across a host of arenas, including telecommunications, water, and other critical lifelines. In this review of related studies, those works with greatest relevance are discussed.

A number of works consider vulnerability of transportation systems (see, for example, Taylor and D'Este 2003; Lleras-Echeverri and Sánchez-Silva 2001; Berdica 2000), where a sudden event may occur that reduces the performance of the network components or significantly impacts demand for use of services offered. Berdica (2002) defines vulnerability as susceptibility to disruptions that could cause considerable reductions in network service or the ability to use a particular network link or route at a given time. Networks that cannot quickly recover from a disruption with minimal reduction in service are deemed more vulnerable than those with quicker recovery time and lower overall experienced disruption. No method for the quantification of this measure is provided. Srinivasan (2002) discussed the potential of developing a quantitative framework for vulnerability assessment. Jenelius, Petersen, and Mattsson (2006) argued that road network vulnerability is composed of the probability and consequences (represented by increased generalized travel cost) of single or multiple link failures. Although numerous attempts to measure vulnerability exist in the literature, vulnerability for transportation networks is still a rather ambiguous term, lacking a clear definition and methodology for its quantification.

Because vulnerability is often employed only qualitatively, quantitative measures of reliability have been used to gain insight into a system's level of vulnerability. Berdica (2002) argued that vulnerability in the road transportation system is reliability as a measure of both probability and consequences of failure. Husdal (2004) linked vulnerability and reliability from a cost-benefit perspective, with vulnerability the cost and reliability the benefit value. Husdal argued that vulnerability is equivalent to "non-reliability" in certain circumstances. Dayanim (1991) argued that it was mandatory to incorporate reliability criteria into network design processes so as to meet disaster recovery requirements. A variety of reliability measures have been implemented for transportation systems to measure their intended functions under uncertainties. For example, connectivity reliability is defined as the probability that the network nodes remain connected

(Iida 1999). Travel-time reliability is concerned with the probability that a trip can reach its destination within a given period (Bell and Iida 1997). Clark and Watling (2005) computed systemwide travel-time reliability based on the probability distribution of network travel time under variable demand. Capacity reliability (Chen et al. 2002) is defined as the probability that the network can adapt to external changes while maintaining a given service level. Elefteriadou and Cui (2007) provided a review of a host of definitions of travel-time reliability proposed in the literature.

Another relevant measure is flexibility. Goetz and Szyliowicz (1997) suggested that flexibility can be useful in coping with uncertainty. Although primarily used in manufacturing systems analysis, several works have considered its application in assessing transportation systems. Feitelson and Salomon (2000) discussed flexibility from the infrastructure manager's perspective and define flexibility as the network's ability to adapt to changing circumstances and demands. Cost and ease of building additional network capacity are considered. Cho (2002) defined capacity flexibility as the ability of a traffic network to expand its capacity to accommodate changes in demand for its use while maintaining a satisfactory level of performance. Morlok and Chang (2004) extended this definition from the perspective of external changes in both travel demand (traffic volume and pattern) and network capacities. Sun, Turnquist, and Nozick (2006) further measured flexibility in a more complicated problem setting, where future traffic patterns, service deterioration, and stochastic demand are considered.

Diverse measures of resilience have been proposed for measuring the performance of engineering systems. For example, resilience is defined as the number of failures that a computer network can sustain to remain connected (Najjar and Gaudiot 1990). For supply networks, resilience is described as the ability to cope with externalities and restore normal operations (Rice and Caniato 2003). Konak and Bartolacci (2007) used traffic efficiency, defined as the expected percent of the total traffic that a network can manage, as a measure of resilience for telecommunication networks. McManus et al. (2007) define organizational resilience as a function of system awareness, identification and management of the most critical system components, and adaptability. A measure of resilience is introduced by Murray-Tuite (2006) in the context of transportation. In her work, resilience is viewed as a network characteristic that indicates how well the traffic network performs under unusual circumstances. Resilience is seen as having 10 dimensions (redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and the ability to recover quickly) that are individually computed based on results of simulation runs.

One can view the measures of reliability, flexibility and resilience as indicators of vulnerability. Such measures from prior works have wide interpretation, are often intertwined, and are sometimes interchangeable. Their definitions vary, although the majority involve some element of risk because they are defined based on a combination of the probability of the occurrence of the disruptive event, the negative impacts of the disruption, and aspects of network performance under disruption.

In this paper, resilience is defined as a network's capability to resist and recover from a disruption or disaster. This definition reflects both the network's inherent ability to cope with disruptions by means of its topological and operational attributes and potential immediate actions that may be taken in the aftermath of the disruption that would otherwise not be considered. For example, a link may be constructed that did not exist in the original network. Because recovery is the process of reconstructing, restoring, and reshaping the physical, social, economic, and natural environment through predisaster planning and postdisaster actions (Havidán, Enrico, and Russell 2007), the proposed resilience measure considers both predisaster planning through consideration of the existing network topology and attributes and immediate postdisaster actions (i.e., potential recovery activities). Although numerous definitions of indicators of network performance exist in the literature, only qualitative measures of resilience related to business contingency planning exist that explicitly consider the impact of such postdisaster actions (Havidán, Enrico, and Russell 2007). No prior work exists that provides the means of quantifying such a measure.

3. Definition and Problem Formulation

Although the proposed definition of resilience and method for its quantification can be applied widely, the focus herein is on assessment of an intermodal freight transport system. Such systems involve multiple modes (truck, rail, and marine) in the movement of cargo between their origins and destinations. In this section, a definition of resilience for intermodal freight transport networks is introduced and a mathematical formulation that seeks an optimal set of recovery activities to undertake in the immediate aftermath of a disaster, such that the network's resilience is maximized and budget constraints are met, is proposed. Formulation and solution of this mathematical program relies on a multimodal network representation described in this section.

3.1. The Resilience Indicator

Measurement of network resilience of an intermodal freight transport system should take into consideration the level of effort (cost, time, resources) required to return the network to normal functionality (or a fixed portion thereof, e.g., 90% functionality) or the impact of a given level of effort (in terms of cost, time, resources) on restoring the network to its original level or fraction thereof of functionality (ability to handle demand D by time T_0). Rose (2004) describes resilience as consisting of two components: inherent and adaptive. In this regard, the network resilience indicator defined herein consists of inherent network properties, e.g., redundancies, and a set of adaptive actions, i.e., recovery activities. With this in mind, network resilience, α, is defined in Equation (1) as the postdisaster expected fraction of demand that, for a given network configuration, can be satisfied within specified recovery costs (budgetary, temporal, and physical).

$$\alpha = E\left(\sum_{w\in\mathbf{W}} d_w \Big/ \sum_{w\in\mathbf{W}} D_w\right) = \frac{1}{\sum_{w\in\mathbf{W}} D_w} E\left(\sum_{w\in\mathbf{W}} d_w\right), \quad (1)$$

where d_w is the maximum demand that can be satisfied for origin-destination (O-D) pair w postdisaster, and D_w is demand that can be satisfied for O-D pair w predisaster. This definition also recognizes that arc capacities depend on the characteristics of the disruption-causing event and therefore cannot be known a priori with certainty. Thus, if any network attribute that impacts its computation is random, as is the case with arc capacities, d_w is a random variable. The set of conceivable disaster events, each with stochastic outcomes in terms of network attributes, is considered in the computation of α.

3.2. Network Representation

A network representation of the intermodal system is used, given by $G = (N, A)$, where $N = \{1, \ldots, n\}$ is the set of nodes, $A = \{(i, j) \mid i, j \in N\}$ is the set of directed arcs. G consists of subnetworks, one for each mode, where transfers between modes take place along transfer arcs connecting intermodal terminals of the various modes, as shown in Figure 1.

Each modal or transfer arc $a \in A$ has associated with it a positive capacity, denoted by c_a, with integral domain and range, and a positive traversal (or transfer) time τ_a. The capacity of each modal arc represents the number of shipments that can be transported along the arc, and the capacity of each transfer arc represents the number of shipments that an intermodal terminal can handle. Note that because the type and timing of the event and its impact cannot be known a priori with certainty, c_a and τ_a are random variables.

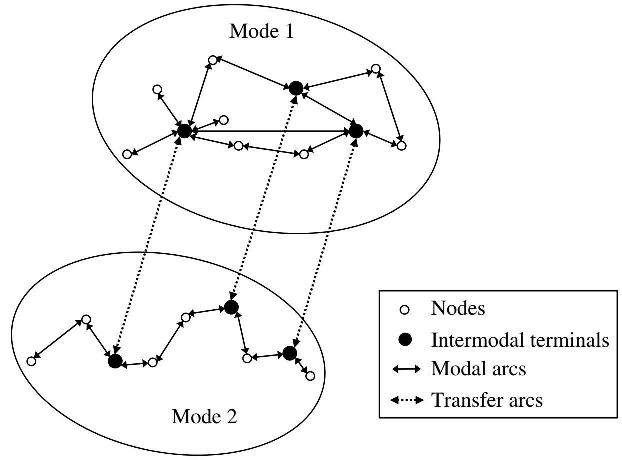

Figure 1 Intermodal Network Representation

A set of O-D pairs, W, is also given. Each O-D pair $w \in W$ has an origin $r(w)$, a destination $s(w)$, and a given demand, i.e., number of shipments, D_w, to be shipped between its origin and destination. A path is defined as an acyclic chain of arcs. A shipment can only be transported along a path with the same origin and destination as the shipment. Let P_w be the index set of all paths that start from $r(w)$ and end at $s(w)$. The time for traversing path $p \in P_w$ is computed from the sum of traversal times of its constituent arcs.

Additional notation employed in the mathematical formulation of the network resilience problem are defined as follows:

- $\not{K}$ = the set of candidate recovery activities, $\not{K} = \{k = 1, 2, \ldots, K\}$;
- Δc_{ak} = change in capacity of link a if recovery activity k is implemented;
- t_{ak} = travel time of link a that can be reached if recovery activity k is implemented; noting that link travel time can be improved if a recovery activity is undertaken;
- q_{ak} = time needed to implement recovery activity k on link a;
- Q_p^R = maximum implementation time of recovery activities taken along path p;
- $T_w^{\max}$ = maximum allowable traversal time for O-D pair w;
- b_{ak} = cost of implementing recovery activity k on arc a;
- B = maximum allowable cost of recovery activities;
- δ_{ap} = in path-link incidence matrix; $\delta_{ap} = 1$ if path p uses link a and $\delta_{ap} = 0$ otherwise.

Decision variables:

- f_p = number of shipments transported on path p;
- y_p = binary variables indicating whether or not path p will suffice given corresponding $T_w^{\max}$, where $p \in P_w$;

$\bar{d}_w =$ number of shipments that cannot be satisfied for O-D pair w;

$\gamma_{ak} =$ binary variables indicating whether or not recovery activity k is undertaken on arc a.

3.3. Problem Formulation

The network resilience problem can be formulated as a stochastic mixed-integer program shown in (R): (2)–(11), where an outcome $\tilde{\xi}$ sets the realization of random variables ξ, referred to as a network state. Program (R) contains integer variables, representing the selection of recovery activities on corresponding arcs and the selection of paths carrying flow, and continuous variables, representing the flow of shipments along each path and demand that cannot be satisfied for each O-D pair.

$$(R) \quad \min \; E_{\xi}\left[\sum_{w\in W} \bar{d}_w(\tilde{\xi})\right] \tag{2}$$

$$\text{s.t.} \quad \sum_{p\in P_w} f_p(\tilde{\xi}) = D_w - \bar{d}_w(\tilde{\xi}) \quad \forall\, w \in W, \tag{3}$$

$$\sum_{w\in W}\sum_{p\in P_W} \delta_{ap} f_p(\tilde{\xi}) - c_a(\tilde{\xi}) - \sum_k \Delta c_{ak}\gamma_{ak}(\tilde{\xi}) \le 0 \quad \forall\, a\in A, \tag{4}$$

$$\sum_{a\in P}\tau_a(\tilde{\xi}) + \sum_{a\in P}\sum_k \big(t_{ak}(\tilde{\xi}) - \tau_a(\tilde{\xi})\big)\gamma_{ak}(\tilde{\xi}) + Q_p^R(\tilde{\xi}) \le T_w^{\max}(\tilde{\xi}) + M\big(1 - y_p(\tilde{\xi})\big) \quad \forall\, p\in P_w,\; w\in W, \tag{5}$$

$$f_p(\tilde{\xi}) \le D_w y_p(\tilde{\xi}) \quad \forall\, p\in P_w,\; w\in W, \tag{6}$$

$$Q_p^R(\tilde{\xi}) - q_{ak}\gamma_{ak}(\tilde{\xi}) \ge 0 \quad \forall\, a\in p,\; k\in K, \tag{7}$$

$$\sum_a\sum_k b_{ak}\gamma_{ak}(\tilde{\xi}) \le B, \tag{8}$$

$$\sum_k \gamma_{ak}(\tilde{\xi}) \le 1 \quad \forall\, a\in A, \tag{9}$$

$$f_p(\tilde{\xi}),\; \bar{d}_w(\tilde{\xi}) \ge 0 \quad \forall\, p\in P_w,\; w\in W, \tag{10}$$

$$\gamma_{ak}(\tilde{\xi}),\; y_p(\tilde{\xi}) \in \{0,1\} \quad \forall\, a\in A,\; k\in K,\; p\in P_w,\; w\in W. \tag{11}$$

The objective (2) of program (R) seeks to minimize the expected portion of demand that cannot be accommodated, i.e., it maximizes the expected number of shipments that can be sent from their origins to their destinations. To compute this expectation, $\sum_{w\in W}\bar{d}_w$ is evaluated over all possible realizations of random arc attributes.

Constraints (3) are flow conservation constraints. Constraints (4) are capacity constraints, restricting flow on each arc to be less than the capacity resulting from the impact of the event and recovery actions that are taken. Constraints (5) and (6) are level-of-service (LOS) constraints requiring that the time each shipment spends traversing a path $p \in P_w$ not exceed a given maximum duration $T_w^{\max}(\tilde{\xi})$ and specific circumstances (i.e., network state $\tilde{\xi}$). M is a sufficiently large positive constant. The time for traversing each path $p \in P_w$ is composed of three parts: constituent link travel times under postdisaster conditions, the maximum time required to implement recovery activities along constituent links (defined by Constraints (7)), and reductions in link travel times due to recovery actions. It is assumed that all recovery activities begin simultaneously, immediately after the event, and any link chosen to undergo a recovery action will be out of service during the action's implementation. Time required to initiate an activity is included in its implementation time. Constraints (5) and (6) provide a linear implementation of the disjunctive constraints:

$$f_p\left(\sum_{a\in P}\tau_a + \sum_{a\in P}\sum_k (t_{ak}-\tau_a)\gamma_{ak} + Q_p^R - T_w^{\max}\right) \le 0.$$

Constraint (8) requires that the total cost of the selected recovery actions does not exceed a given budget. Constraints (9) require that only one recovery activity, representing a set of recovery actions, can be selected for each arc. This ensures that conflicting actions will not be simultaneously chosen. Nonnegativity and integrality restrictions are given in constraints (10)–(11). Constraints (3)–(11) are evaluated for a given network state $\tilde{\xi}$.

It is assumed that the revenue (including future revenue) from completing shipment deliveries in a timely manner in postdisaster circumstances significantly outweighs any savings that might be achieved in selecting optimal paths based on operational costs, and therefore, operational costs are not included in the model. If desired, an additional set of constraints with similar form as constraints (5) can be incorporated in the formulation to limit total operating expenses. This will increase the complexity of the problem, but can be solved with the same solution technique.

Although the formulation does not include pre-event decision variables, a network's resilience level under a given network state, and set of potential remedial actions (if any) can be quantified by employing the formulation under one or more chosen scenarios pre-event. Remedial actions that may be taken pre-event include, for example: adding additional links to the network; ordering spare parts or backup equipment; prepositioning resources in anticipation of potential recovery activities; implementation of advanced technologies; training; and other pre-event actions that can reduce the time and cost required to complete potential recovery activities should they be required postevent. Such pre-event use of the formulation facilitates network vulnerability assessment and further informs the decision maker in taking pre-event action to improve network resilience.

One will note that program (R) includes no first-stage variables. All decisions are taken once the outcome of the random disaster event is known. Thus, the problem can be directly decomposed into a set of independent scenario-specific deterministic problems, denoted by $R(\tilde{\xi})$ for a given network state $\tilde{\xi}$. An NP-hardness result can be derived for problem $R(\tilde{\xi})$ even when the LOS constraints (5) are dropped.

$R(\tilde{\xi})$ is proved to be NP-hard through a reduction from the knapsack problem, a well-known NP-complete problem (Garey and Johnson 1979). An instance of the knapsack problem is given by a finite set $I = \{i_1, i_2, \ldots, i_n\}$ of items, each with a nonnegative weight w_i and value v_i. The problem is to determine if there exists a subset of items $I' \subset I$ with total weight $w(I') \leq W$ and total value $v(I') \geq V$. Accordingly, a network G is constructed with only one O-D pair (s, t) connected by n parallel arcs. Each arc has a nonnegative capacity c_a. Suppose only one recovery activity is available for each arc and will increase the arc capacity by v_a with an implementation cost w_a, a fraction of the budget W. Thus, the instance of the knapsack problem has a solution if and only if there is a flow that sends at least $\sum_{a\in I'} v_a \geq V - \sum_{a\in I} c_a$ shipments from s to t with a cost of at most $\sum_{a\in I'} w_a \leq W$. This transformation can be achieved in polynomial time, proving that problem $R(\tilde{\xi})$ is NP-hard.

4. Solution Technique

To measure network resilience for a given network topology and associated operating characteristics, as well as a given set of potential recovery activity options, problem $R(\tilde{\xi})$ can be solved directly; however, this may require extraordinary effort. The number of variables is large, even for midsize instances. Thus, a framework employing Benders decomposition, column generation, and Monte Carlo simulation is proposed that considers a manageable number of network states. For a given scenario (i.e., event), the joint probability distributions of the random arc capacities and travel times are assumed to be known. For each scenario considered, Monte Carlo simulation is used to generate the values of random variables required to specify the set of possible network states, while preserving distribution properties (§4.2). A Benders decomposition technique that employs column generation in the solution of a set of subproblems is developed to find the maximum demand that can be satisfied for the given network state. Network resilience is computed from the expected value of the weighted sum of the maximum level of satisfied demand achieved for each replication as in Equation (1). The solution technique is discussed in detail next.

4.1. Solving Problem $R(\tilde{\xi})$

4.1.1. Benders Decomposition. Benders decomposition (Benders 1962) is performed on program $R(\tilde{\xi})$, a mixed-integer program over binary variables γ_{ak}. The original problem is reformulated into a subproblem containing the continuous path flow variables and a master problem containing the binary recovery activity selection variables. Benders cuts are generated by solution of the subproblem and are added to the relaxed master problem at each iteration, progressively constraining the relaxed master problem. The cuts reduce the number of flow variables that must be considered, even at the expense of increasing the number of constraints.

For simplicity, program $R(\tilde{\xi})$ can be transformed into a network flow problem with a single source and single sink by adding a super source r connecting to each source node $r(w)$ by arcs with capacity D_w and travel time $(T^{\max} - T_w^{\max})$, where $T^{\max}$ is the maximum allowable travel time for any r-s path with positive flow, and a super sink s connected to each sink node $s(w)$ by arcs with capacity $\sum_{w\in W} D_w$ and zero travel time. Denote the path set between r and s by P. The exact algorithm presented hereafter is applied in solving this r-s network flow problem.

Let γ be the 0-1 vector satisfying constraints (8) and (9), and let Λ be the set of valid γ. For given $\hat{\gamma} \in \Lambda$, the primal subproblem can be stated as follows:

$$SR(\hat{\gamma}): \quad \max \sum_p f_p \tag{12}$$

$$\text{s.t.} \sum_{p\in P} \delta_{ap} f_p \leq c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak} \quad \forall a \in A, \tag{13}$$

$$\sum_{a\in P} \tau_a + \sum_{a\in P}\sum_k \big(t_{ak} - \tau_a\big)\hat{\gamma}_{ak} + \max_{a\in p} q_{ak}\hat{\gamma}_{ak} \leq T^{\max} + M\big(1 - y_p\big) \quad \forall p \in P, \tag{14}$$

$$f_p \leq D y_p \quad \forall p \in P, \tag{15}$$

$$f_p \geq 0, \quad y_p = \{0, 1\} \quad \forall p \in P. \tag{16}$$

Problem $SR(\hat{\gamma})$ is a path-flow based formulation of a maximum flow problem with side constraints.

For the given $\hat{\gamma}$, the path set P can be separated into two disjoint subsets: $P_1 = \{p \mid \sum_{a\in P} \tau_a + \sum_{a\in P}\sum_k (t_{ak} - \tau_a)\hat{\gamma}_{ak} + \max_{a\in p} q_{ak}\hat{\gamma}_{ak} \leq T^{\max}, \forall p \in P\}$, the set of paths between r and s that satisfy LOS constraints, and $P_2 = \{p \mid \sum_{a\in P} \tau_a + \sum_{a\in P}\sum_k (t_{ak} - \tau_a)\hat{\gamma}_{ak} + \max_{a\in p} q_{ak}\hat{\gamma}_{ak} > T^{\max}, \forall p \in P\}$, the set of paths between r and s that do not satisfy LOS constraints. By considering only P_1, subproblem $SR(\hat{\gamma})$ can be reformulated with only continuous decision variables given by subproblem $LSR(\hat{\gamma})$:

$$LSR(\hat{\gamma}): \quad (12)$$

$$\text{s.t.} \quad \sum_{p\in P_1} \delta_{ap} f_p \le c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak} \quad \forall a \in A, \tag{17}$$

$$f_p \ge 0, \quad \forall p \in P_1. \tag{18}$$

The dual subproblem is given as follows:

$$DSR(\hat{\gamma}): \quad \min \sum_{a\in A} \left(c_a + \sum_k \Delta c_{ak} \hat{\gamma}_{ak}\right) \pi_a \tag{19}$$

$$\text{s.t.} \quad \sum_{a\in p} \pi_a \ge 1 \quad \forall p \in P_1, \tag{20}$$

$$\pi_a \ge 0 \quad \forall a \in A, \tag{21}$$

where π_a are the dual variables associated with constraints (17). The primal subproblem $LSR(\hat{\gamma})$ is always feasible, because 0 is always a feasible solution, and a feasible solution for $DSR(\hat{\gamma})$ can be readily obtained. Thus, by the weak duality theorem, the primal and dual subproblems are bounded.

The Benders master problem is obtained by replacing constraints (4)–(7) by Benders cuts (23). Constraints (23) are optimality cuts that ensure that affected nonoptimal solutions are excluded. Let D denote the polyhedron defined by constraints (20) and P_D be the set of extreme points of D. Introducing the additional free variable Z, program $R(\tilde{\xi})$ can be reformulated as the following equivalent problem MR.

$$MR: \quad \max \ Z \tag{22}$$

$$\text{subject to} \quad Z - \sum_{a\in A}\sum_{k\in K} \Delta c_{ak} \pi_a \gamma_{ak} - \sum_{p\in P_w} D_w \pi_p y_p \le \sum_{a\in A} c_a \pi_a, \quad \forall \pi \in P_D, \tag{23}$$

$$(8), (9), (11).$$

Constraints (23) need not be exhaustively enumerated, because most of the constraints will be inactive in the optimal solution. Thus, a relaxation of problem (MR), denoted as (RMR), can be obtained by dropping constraints (23) and iteratively adding them to the relaxation until optimality is achieved.

To improve (RMR), constraints (8) can be replaced by (8′):

$$B - \sigma < \sum_a \sum_k b_{ak} \gamma_{ak}(\omega) \le B, \tag{8′}$$

where σ is the maximum implementation cost over all recovery activities. One can show that constraints (8′) are more restrictive than (8) for problem (RMR), thus creating a smaller feasible region. Moreover, the optimal solution will not be cut off by this inequality. This can be shown by considering the following. Suppose an optimal solution (γ^*, y^*, f^*) to program (R) with objective function value z^* exists such that $B - \sum_a \sum_k b_{ak} \gamma^*_{ak}(\omega) \ge \sigma$; then there exists at least one arc a for which $b_{ak} \le \sigma$ and $\sum_k \gamma^*_{ak} = 0$. The corresponding recovery activity with cost $b_{ak} \le \sigma$ can be undertaken without violating constraints (3)–(11). The resulting solution is a feasible solution with objective function value no greater than z^*.

4.1.2. Column Generation for Subproblem Solution. Primal and dual subproblems are solved by iteratively generating Benders optimality cuts that constrain problem (RMR). Both subproblems $LSR(\hat{\gamma})$ and $DSR(\hat{\gamma})$ are path-flow based formulations. The number of path-flow variables grows exponentially with the size of the network, making both problems difficult to solve. Thus, a column-generation based technique (see Wolsey 1998 for general background) is applied that narrows in on a limited set of paths. The column generation algorithm presented in this section is an iterative method, which takes advantage of subproblem $LSR(\hat{\gamma})$'s structure and constructs a series of subproblems, each increasingly more restricted. At each step, new paths (i.e., columns) are generated, expanding the restricted subset of P_1, defined in the previous subsection. The algorithm terminates when no new path (i.e., column) can be identified for inclusion in this subset.

The column generation process starts with an initial subset of path variables. The reduced cost of f_p is computed as $\bar{c}_p = 1 - \sum_{a\in p} \pi_a$. The optimality condition is given by $\bar{c}_p \le 0$, $\forall p \in P_1$. If there exists a path $p \in P_1$ such that $\bar{c}_p > 0$, then f_p should be chosen as the variable that enters the limited path set. The new column will be identified by considering which constraints in the dual subproblem are most violated. If the constant 1 is ignored in computing reduced costs, the problem of choosing the entering column is a shortest-path problem with a path traversal time constraint. A variety of algorithms have been proposed in the literature to address this problem (e.g., Aneja, Aggarwal, and Nair 1983; Handler and Zang 1980; Desrosiers et al. 1995). In implementations described in §5, a label-setting algorithm based on dynamic programming concepts that can be attributed to Dumitrescu and Boland (2003) is used.

4.1.3. Upper and Lower Bounding. The Benders relaxed master problem (RMR) becomes increasingly constrained as Benders cuts are added, providing an upper bound on the objective value of the original problem that is nonincreasing with every iteration. Moreover, a feasible solution is obtained, generating a lower bound, and possibly improving the best lower bound, at each iteration. The algorithm stops when upper and lower bounds meet. Thus, tight bounds are important to accelerating the convergence of the algorithm.

An initial upper bound on problem (*RMR*) is obtained by relaxing binary variables γ_{ak} $\forall a, k$ in problem $R(\tilde{\xi})$ and solving the corresponding relaxed problem, a constrained optimal capacity expansion problem with linear cost functions. If path constraints are relaxed, the capacity expansion problem can be solved in polynomial time. Thus, a similar technique is used to solve the Benders subproblem, subproblem $LSR(\hat{\gamma})$, is applied to solve this relaxed problem and generate the initial upper bound.

To generate an initial feasible solution, and an initial lower bound, to problem (*RMR*), the following lexicographic ordering rules can be applied, where γ_{ak} is obtained during the process of determining an initial upper bound on problem (*RMR*): (1) rank all the γ_{ak} variables by their values, giving priority to those with the largest capacity when ties exist; and (2) obtain a limited set of γ_{ak} variables from the order produced in (1) with the maximal value of $\sum_{a,k} b_{ak}$ such that $\sum_{a,k} b_{ak} \le B$ and set $\gamma_{ak} = 1$ for all variables in the set.

The lower bound does not follow an increasing trend, because the objective function value obtained from consecutive iterations may vary significantly. To address this issue, local branching proposed by Fischetti and Lodi (2003) is applied to identify a feasible solution that results in an improved lower bound. Rei et al. (2009) discussed the possibility of using local branching to increase the speed of Benders decomposition. Their idea is to seek an improved feasible solution (and improved lower bound) by considering a small subregion of the feasible space surrounding the previously identified feasible solution. Given feasible solution $\{\tilde{\gamma}_{ak}\}_{a,k}$ of problem (*RMR*) and a positive integer parameter k, the local branching constraint can be written as

$$\Delta(\gamma, \tilde{\gamma}) = \sum_{\tilde{\gamma}_{ak}=1} (1 - \gamma_{ak}) + \sum_{\tilde{\gamma}_{ak}=0} \gamma_{ak} \le k. \qquad (24)$$

The local branching constraint divides the feasible region into two branches. Branching strategies are used continuously to generate better solutions until no improved solution can be found or a prescribed computational time limit is reached. Through local branching, multiple Benders cuts can be generated at each iteration.

4.1.4. Benders Decomposition Algorithm. Details of the Benders decomposition algorithm built on concepts described in previous subsections and proposed for solution of problem $R(\tilde{\xi})$ are described next.

1. Set $t := 1$ and $P_D^1 := \varnothing$. Solve the relaxation of problem $R(\tilde{\xi})$ (γ is relaxed) to generate an upper bound, UB. Generate a feasible solution according to lexicographic ordering rules.

2. Solve the Benders master problem and subproblems.

2.1. Solve problem (RMR^t). Let γ^t be an optimal solution of objective function value Z^t. $UB = \min\{UB, Z^t\}$. Use local branching to identify feasible solutions.

2.2. Solve subproblem $LSR(\hat{\gamma}^t)$ via column generation.

2.2.1. Let the initial column be given by the shortest r–s path. If the LOS constraint is not satisfied for the shortest path, stop.

2.2.2. Construct the restricted master problem using identified paths (i.e., columns) and solve to generate dual prices.

2.2.3. Use the dual prices obtained in Step 2.2.2 to solve the constrained shortest-path problem. If $\bar{c}_p \le 0$, $\forall p \in P_1$, stop; otherwise, identify columns (i.e., paths) for which $\bar{c}_p > 0$, add the new column to the master problem, and return to step 2.2.2.

3. Let $\{f_p^t\}$ be a primal optimal solution and z^t be the subproblem objective function value. Lower bound, $LB = \max\{LB, z^t\}$. If $UB = LB$, then (γ^t, f_p^t) is an optimal solution to problem $R(\tilde{\xi})$, stop; otherwise, set $P_D^{t+1} = P_D^t \cup (\gamma^t, f_p^t)$ and $t = t + 1$. Return to step 2. The algorithm terminates with an optimal solution to problem $R(\tilde{\xi})$.

4.2. Monte Carlo Simulation

In the previous subsection, an exact Benders decomposition technique is proposed for solution of problem $R(\tilde{\xi})$, the deterministic equivalent problem of stochastic program (R). To compute network resilience, Monte Carlo simulation is employed to generate a manageable number of samples (each sample creates an instance of problem $R(\tilde{\xi})$) from random variates defined on the probability space to approximate the expectation of Equation (1). This idea of sample average approximation has been suggested by numerous authors (e.g., Shapiro and Philpott 2007).

Monte Carlo methods are widely used to simulate the random behavior of systems through repeated sampling from random variables with given probability distributions. In an intermodal transport network, dependency among random arc capacities can be expected. For example, an earthquake will impact all transportation facilities in the same area at the same time. Correlation in arc capacity among these adjacent facilities should be expected, and the correlation structure will differ considerably for varying types of events. To preserve the specified correlation structure among the random variables associated with the given event, the employed Monte Carlo method must generate random variates that maintain the same probabilistic characteristics. The approach developed by Chang, Tung, and Yang (1994) is applied herein to generate multivariate correlated random variates of arc capacities (see Appendix A for additional detail).

This method has been previously applied in the context of transportation systems to generate random interdependent link capacities (Chen et al. 2002). After a realization of the random parameters is generated, the exact method proposed in the previous subsection can be applied to solve each program $R(\tilde{\xi})$ for the given realization. The individual objective function values are collected to compute the resilience indicator α.

5. Numerical Experiments

Results of two sets of numerical experiments are presented in this section. The first set involved an intermodal freight network in the Western United States. These experiments were designed to illustrate the resilience concept proposed herein. The second set was conducted on four carefully designed hypothetical networks to study the role a network's structure plays in resilience. The proposed solution technique described in §4 was implemented in Microsoft Visual Studio C++ 6.0 language with the ILOG CPLEX callable library 9.1 (2005). Experiments were run on a personal computer with Pentium (4) CPU 3.20 GHz and 2.00 GB of RAM.

5.1. Illustration on Double-Stack Container Network

The solution technique is applied on the 8-node, 12-arc double-stack container network as depicted in Figure 2. This rail network covers a wide area in the Western United States. It involves 17 potential O-D pairs and includes nodes representing such cities as Chicago, Los Angeles, and Houston. In double-stack operations, containers are stacked one on top of another in layers of two. Additional detail concerning the network topology can be found in Morlok and Chang (2004) and Sun, Turnquist, and Nozick (2006). Container travel times, including travel time along arcs and handling in railway terminals, are defined for each O-D pair. Although not depicted in Figure 2, intermodal connections exist at every node (i.e., city) in the network, connecting the rail terminals with the highway network. A virtual highway link between every O-D pair was employed to model highway operations. Their travel times were set using estimates from GoogleMap, and capacity was assumed to be sufficient to handle all freight transport demand for the region.

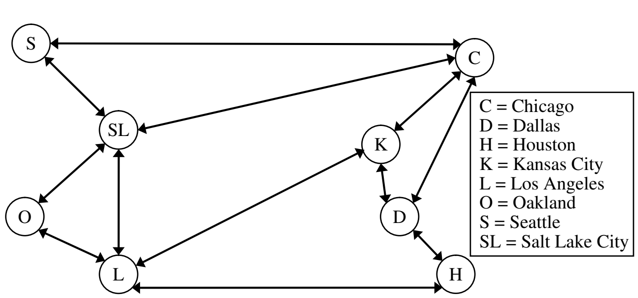

Figure 2 Western U.S. Double-Stack Container Network

Five types of scenarios were considered as described in Table 1. Factors considered in the construction of these scenarios include the disaster classification, consequences of the disaster in terms of impact on arc capacities and intermodal operations, and an appropriate correlation matrix for the given disaster classification. In all scenarios considered, it was assumed, for simplicity, that only rail links were impacted or can be addressed through recovery activities.

For areawide disasters such as might arise under scenarios involving an earthquake (i.e., scenario 4), highway links may suffer similar disruption as rail links in affected subregions. For simplicity, in the experiments the duration required to traverse the highway links where a terminal exists in an affected subregion is increased by 30% from the average to account for likely delays incurred along the highway links. Greater increases might be considered, where devastation due to the disaster event is found to be very significant, and more detailed modeling of traffic impacts can be employed for greater accuracy.

Dependencies among capacity random variables, which specify each scenario, are a function of the disaster classification. For instance, a snow storm will simultaneously affect all network components in a region, leading to strong correlation among arc capacity random variables of adjacent arcs. A terrorist attack on a particular location will cause serious damage to one or more network components in a small area. Monte Carlo simulation is used to generate the realization of interdependent arc capacities (specifying a network state) for a given scenario. Different correlation matrices are applied for each distinct scenario. Arc capacities, c_a, $\forall a \in A$, are assumed to be uniform random variables, each with a specified range $[l_a, u_a]$.

Table 1 Characteristics of Test Scenarios

Scenario	Description	Details on arc dependencies
1	Bombing	Randomly selected links in the network are nonfunctioning.
2	Terrorist attack	Negative impact on arc capacities, large negative impact close to the emergency scene, less impact away from the emergency scene.
3	Flood	Multiple connected links nonfunctioning over a large area.
4	Earthquake	Randomly selected links over a large area are negatively impacted.
5	Intermodal terminal attack	Flow into and out of terminals in Chicago and Los Angeles significantly impacted due to an attack.

Several recovery activities, defined as activities that can be taken in the immediate aftermath of a disaster to mitigate the disaster's negative impacts and restore network capacity, are considered for implementation. Examples of potential recovery activities include, among others, rerouting shipments employing alternative transport modes (e.g., from rail to truck); restoring and repairing damaged infrastructure; building temporary roadways; instituting access control to an impacted area; utilizing spare parts or equipment, as well as extra personnel; and employing advanced traffic management strategies. Six hypothetical recovery activities were considered in the experiments, each with different duration, cost, and effect as delineated in Table 2. Although the recovery actions are generically defined, these actions are consistent with activities that might be undertaken to mitigate the impact of the specific disasters considered in scenarios 1 through 5. For example, the changes created through recovery activity 2 are consistent with high-cost, short-duration construction actions associated with capacity restoration along links of the network. Improvements rendered through recovery activity 3 may be consistent with the use of spare equipment, thus, the low cost, but relatively moderate impact.

Intermodal networks may be more vulnerable than single-mode networks in terms of exposure to risk, but intermodal options provide greater opportunity for recovery in the immediate aftermath of disaster. Recovery option 6 was designed to illustrate the impact of recovery opportunities that exist by virtue of intermodal connections, though needed as a consequence of an attack on intermodal terminals or other network link (scenario 5). An attack on an intermodal terminal would impact the ability to process intermodal containers. To accommodate affected shipments, containers that were to be shipped within the rail network through the impacted terminal can be rerouted along alternative railway lines or might be handled through truck transport along the highway links. Changes in arc capacity, implementation duration, and costs resulting from and required for implementation of recovery activity 6 are consistent with a mode shift from rail to truck as might be required in response to a scenario like scenario 5. The high cost of transfer is expected due to the cost of terminal operations and the additional expenses associated with the last-minute hiring of trucking companies for what might be considered emergency circumstances. This last recovery activity assumes that capacity for transfer to truck is sufficient to meet all new demand. Alternate recovery actions might be considered under scenarios in which this is not the case.

Table 2 Characteristics of Recovery Activities

Recovery activities	Recovery activity duration (units)	Cost (units)	Recovery activity effect (% increase in affected capacity)	Applicable for arcs
1	2	6	10	1–12
2	1	10	10	1–6
3	6	1	5	7–12
4	4	4	10	1, 3, 5, 7, 9, 11
5	3	8	15	2, 4, 6, 8, 10, 12
6	3	10	Return to original capacity	1–12

Assumptions regarding the durations and costs of recovery activities are given in Table 2. For each railway arc, it was assumed that pre-event arc travel times and capacities are known. Postevent capacities are randomly generated in accordance with the characteristics of the event and changes in travel times resulting from reduced capacity are determined as a function of change in capacity. Any change in arc travel time that results from a recovery activity is assumed to be directly correlated with improvements in arc capacity resulting from that activity. For example, under the first scenario, if a recovery activity results in x percent increase in capacity along an arc, it is assumed that the arc travel time decreases by $0.1x$ percent. The total budget is assumed to be 30 units, and travel-time limitations are set for individual O-D pairs to a value slightly larger than the time required by the shortest path.

To determine an appropriate sampling size for the Monte Carlo technique, 10,000 iterations were run for a test case from which the objective function value was collected for each iteration. It is noted that the average objective function value steadily increases in the early iterations of the simulation and was determined to stabilize after approximately 5,000 iterations. Thus, a stopping criterion of 5,000 iterations was employed in all remaining tests. One might alternatively consider the mean square error and maximum error differences in the resilience distribution in determining an appropriate iteration in which to terminate the procedure.

Computational results of the experiments are given in Figure 3. To compare the impact of recovery activities on resilience level under varying scenarios, post-event resilience is measured assuming that post-event conditions will remain if no recovery activity is taken. Note that the resilience indicator proposed herein was designed for pre-event analyses. Thus, one could compute resilience of the double-stack container network as defined in prior sections, where all potential scenarios are considered in the computation.

The results show that recovery activities can lead to significant improvement in resilience level, indicating the importance of recovery activities in terms of network performance in the aftermath of a disaster. Over all tested scenarios, an average improvement

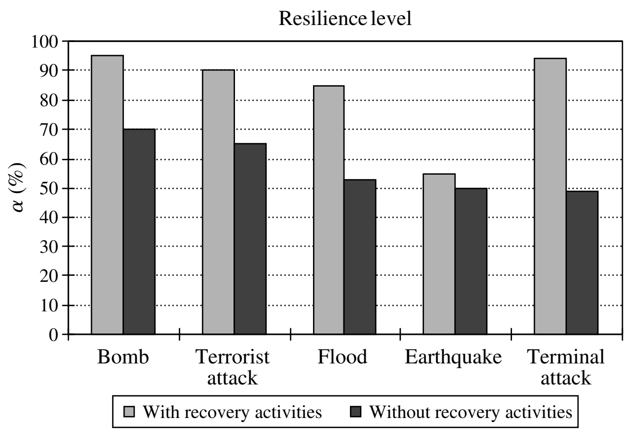

Figure 3 Computational Results for Different Scenarios

in resilience of approximately 57% (with a range of 10% to 141%) was found as a consequence of considering recovery activities. It is worth noting that the resilience level is much smaller for scenario 4, where an earthquake is presumed to have occurred, than for other scenarios. This is due both to the greater link capacity degradation experienced in the scenario and the presumed effectiveness of recovery activities. For example, in an earthquake, it is presumed that the impact of the disaster event on both rail and highway is similarly significant. The wide difference between resilience levels with and without recovery activity options associated with scenario 5, involving attacks on intermodal terminals in Chicago and Los Angeles (perhaps the busiest terminals in the network), illustrates the magnitude of the potential role of recovery activities on system performance.

To further illustrate the proposed concept of resilience, intermodal network implementations of network reliability and flexibility as defined in Chen et al. (1999, 2002), Morlok and Chang (2004), Sun, Turnquist, and Nozick (2006) are computed under each scenario for the illustrative rail network and are compared with resilience. Chen et al. (1999, 2002) define reliability as the probability that the network can accommodate the demand while maintaining a given service level, and Morlok and Chang (2004) (also adopted in Sun, Turnquist, and Nozick 2006) define flexibility as the ability to efficiently utilize the capacity of a traffic network to accommodate variations in demand while maintaining a satisfactory LOS.

To compute these measures of reliability and flexibility, a bilevel optimization model was constructed in which lower-level decisions involve the assignment of traffic to the network, and upper level decisions involve the determination of the maximum demand multiplier (referred to as the reserve capacity) permissible given problem constraints. Similar constraints employed to measure resilience are employed in these models. Reliability is equal to the probability that the maximum multiplier can be set to a value greater than the base demand level given random link capacities. Flexibility, on the other hand, is set to the expected value of the maximum multiplier divided by the base demand level.

Although, like resilience, reliability and flexibility are typically measured with no knowledge of a particular disaster event, to illustrate the impact of recovery activities on these network performance measures, postevent values are computed. The values of postevent reliability and resilience (considered with and without recovery activities) obtained from the experimental results are recorded in Table 3. While post-event flexibility was computed, the values were very similar to those obtained for reliability and, thus, are omitted.

The values of the network performance metrics given in Table 3 indicate that the measure of resilience when no recovery activities are considered provides similar information to its reliability and flexibility counterparts in all scenarios. When effective recovery activities are available, the reliability measure does not adequately capture a network's resilience level. For example, to mitigate the impact of a disaster caused by a bombing or terrorist attack (scenarios 1, 2, and 5), where highway links are relatively unaffected by the incident, shipments can be shifted from rail to truck. In such circumstances, a network's reliability may be quite low, but its resilience may be quite high. That is, resilient networks are not necessarily reliable. The cost of making a network highly reliable may be much greater than making it highly resilient, because resilience accounts for actions that can be taken in the aftermath of disaster once the disaster's impact is known. To achieve greater reliability, on the other hand, a priori actions must be considered to address all plausible disaster events. Thus, intermodal freight networks, as with other transportation networks, should be designed to meet acceptable levels of both reliability and resilience.

One can construct networks and circumstances for which there is even greater disparity in relative performance (as measured by reliability, flexibility, and resilience) over the various scenarios. For example,

Table 3 Comparison by Performance Metric

		Postevent resilience	
Scenario	Postevent reliability	Without recovery activities	With recovery activities
1	0.65	0.7	0.95
2	0.6	0.65	0.90
3	0.51	0.53	0.85
4	0.48	0.5	0.55
5	0.39	0.39	0.94

it is possible that the resilience of a network under scenario A could be higher than for the network under scenario B, but the reliability of the network under scenario B is higher than it is under scenario A. This may arise, for example, where effective recovery activities under scenario B require greater investment than the budget allows.

5.2. Role of Network Structure in Resilience Level Additional experiments were developed to gain insight into the role of a network's topology in its resilience level given the possibility of disaster occurrence. Network structure and operating characteristics were carefully designed for this purpose. Arcs were treated generically to maintain a maximum level of consistency in all experiments so as to isolate network structure from other features that could impact resilience level. Four network structures were considered: a complete network, where each node pair is connected by two oriented directed arcs with opposite direction; a random network with average degree two and indegree (and outdegree) of each node ranging between one and three; a grid network with a regular grid structure; and a network with multiple hubs, i.e., with three completely connected hubs into which traffic from outlying nodes feed. All networks were created with symmetry, i.e., if an arc originates from node i that is incident on node j, another arc originates at node j that is incident on node i. Table 4 synopsizes the characteristics of these different network topologies. All arcs in all networks were assumed to have capacities of four units that if impacted by disaster either decreased by 50% or 100%, determined randomly assuming a binomial distribution. Travel times were assumed to increase by 100% or 400%, consistent with the chosen capacity reduction.

Three sets of recovery activities were considered under all runs. In the first set, each activity raises the capacity of the arc to which it is applied by one unit, decreases the arc's travel time by two units, requires one unit of time for its implementation, and costs $10. The second set results in increased capacity of two units and decreased travel time of four units. Each activity in this set requires two units of time for its implementation and costs $25. The third set results in increased capacity of three units and decreased travel time of six units. Each activity requires two units for its implementation and costs $50.

Table 4 Network Structures

Networks	No. of nodes	No. of arcs	Average indegree
Complete network	10	90	9
Random network	10	20	2
Grid network	10	30	3
Hub-based network	10	30	3

Three disaster scenarios were considered, the first impacting a randomly chosen set of five arcs, the second impacting a randomly chosen set of half the network arcs, and the third impacting all network arcs. Four budget levels were applied: $0, $200, $500, and $1500. In addition, it is assumed that 16 units of flow (each unit of flow corresponding to, for example, a train) seek the use of the network. These units are evenly distributed across possible O-D pairs. The maximum allowable travel time, $T_w^{\max}$, is assumed to be 50% above path travel-time requirements under normal conditions for all O-D pairs.

Results of these experiments are given in Table 5. Five hundred runs were made for each specification. Each run required less than one minute of computational time.

The results show that for each network, the level of network resilience decreases dramatically with the severity of disruptions and increases with the growth of the recovery budget. If a significant number of arcs in the network are impacted and no recovery activities can be undertaken, all networks exhibit poor performance. That is, the LOS constraints cannot be met for most O-D pairs. With an appropriately set budget, network resilience levels greatly improve. These findings are consistent with those from tests of the double-stack container network.

The experimental results also indicate that complete networks are very resilient. Such networks exhibit high levels of redundancy. Random networks with average indegree or outdegree of two were found to be the least resilient among the four tested network classes. The tested random network included few alternative routes between O-D pairs. Random networks with higher average degree will likely be more resilient. In nearly all tests, the hub-based network was more resilient than the grid network, especially when recovery activities could be undertaken. It appears that the nature of hubs, which are associated with the majority of network connections, plays a role in the network's resilience level. Unless critical links connecting pairs of hubs are impacted, connectivity is maintained for most node pairs even when many links are impacted. If recovery activities can be undertaken, critical links in the hub-based network will consistently be chosen for repair, restoring normalcy with narrowly focused recovery actions.

6. Conclusions and Extensions

From the perspective of both researchers and practitioners, disaster recovery is considered by some to be the least-understood aspect of emergency management (e.g., Berke, Kartez, and Wenger 1993). In this paper, a quantitative, system-level indicator of network recovery capability is proposed. A definition of resilience for intermodal freight networks is

Table 5 Computational Results

Networks	No. of arcs impacted	Budget ($)	Resilience level (%)
Complete	5	0	100
	5	200	100
	5	500	100
	5	1,500	100
	Half	0	99.1
	Half	200	100
	Half	500	100
	Half	1,500	100
	All	0	36.0
	All	200	50.9
	All	500	84.1
	All	1,500	98.5
Random	5	0	72.1
	5	200	98.7
	5	500	100
	5	1,500	100
	Half	0	54.0
	Half	200	59.7
	Half	500	83.4
	Half	1,500	100
	All	0	10.1
	All	200	35.3
	All	500	83.8
	All	1,500	98.3
Grid	5	0	85.5
	5	200	98.7
	5	500	100
	5	1,500	100
	Half	0	62.3
	Half	200	72.5
	Half	500	92.1
	Half	1,500	100
	All	0	15.3
	All	200	47.7
	All	500	71.6
	All	1,500	99.0
Hub-based	5	0	95.2
	5	200	98.8
	5	500	100
	5	1,500	100
	Half	0	65.6
	Half	200	86.8
	Half	500	93.5
	Half	1,500	100
	All	0	12.4
	All	200	75.0
	All	500	94.2
	All	1,500	100

developed and a stochastic, mixed-integer program is formulated. Concepts of Monte Carlo simulation, Benders decomposition, and column generation are integrated to produce a technique for its solution. The solution methodology was employed in a set of computational experiments performed on the double-stack container network in which recovery activities that could be undertaken immediately, requiring relatively short implementation time, were considered. These experiments illustrate the resilience concept and show that postdisaster activities can greatly improve resilience levels, and thus mitigate the negative impact of disasters. The results also indicate that recovery activities are critical to a network's ability to recover and cannot be neglected. Competing measures such as reliability and flexibility that do not consider recovery actions may underestimate the network's ability to cope with unexpected events. In fact, a network may not be very reliable or flexible, but may be resilient or may be reliable or flexible, but not sufficiently resilient.

The resilience concept was also applied in experiments involving four carefully designed networks with dissimilar topological structures, including complete, hub-based, grid, and random structures. Results of these experiments indicate that topological structures with limited redundancies faired worst given a lack of available funds for taking recovery actions; however, even with limited or more modest budgets, improvements in network resilience levels could be obtained. Additionally, greatest improvements were achieved in those networks where few actions might lead to restoration in connectivity between the largest number of O-D pairs, as is the case in a network with hubs. Thus, these experiments indicate that network structures that traditionally fare poorly when reliability is considered can, with only limited recovery action, perform reasonably well, because recovery actions can be focused on highly critical links. This also indicates that predisaster planning might be warranted for such networks to ensure that such actions can be quickly and inexpensively taken in the aftermath of disaster.

Modifications to the problem formulation and solution approach may be desired to consider recovery activities that are available only under specific scenarios. Such modifications would entail adding a dimension to the recovery activity selection variables within the formulation. The proposed solution technique could be immediately adapted for this purpose.

This work was motivated by security and mobility concerns in the Washington, D.C.–New York freight corridor, one of the nation's most critical freight transport lifelines. New York is home to one of the largest concentrations of transportation facilities in the world, including three major airports, dozens of container and intermodal yards, and more than 11,000 miles of highways (Holguin-Veras 2000). With both the nation's capital and a global financial center, this corridor is particularly susceptible to terrorist attack. Moreover, because the corridor runs along the coast, it is susceptible to natural hazards. The proposed solution framework employs an exact procedure over a set of network states for each disaster scenario. Because the network resilience problem given only one possible network state is NP-hard, exact solution for large, real-world networks, such as the Washington, D.C.–New York corridor, will be difficult to obtain. To decrease the computational effort required, one might consider only the highest-priority O-D pairs. Such consideration would require only a nominal change in the objective function. Additionally, in this work, recovery activities associated with individual arcs are considered. Instead of considering all possible combinations of recovery activities associated with all arcs, a subset of these combinations can be considered. Alternatively, a heuristic may be employed for computing the resilience of large networks. The proposed technique can be used to provide exact solution on a set of benchmarks to which the heuristic solutions can be compared.

Specific details of the types of resilience-building activities that can be undertaken prior to, or in the immediate aftermath of, a disaster, such as increasing transportation system diversity and promoting intermodalism, increasing network redundancy and connectivity, hardening facilities to withstand extreme conditions, and preparing backup fleets and personnel, should be further explored. Through sensitivity analysis, it may be possible to identify critical system components and obtain valuable information that can be used in prioritizing activities to be undertaken. Additional efforts may also be expended to extend the proposed resilience concept for use in passenger transport systems.

The focus of this work is on measuring network resilience because it concerns network performance in the immediate aftermath of a disaster. It is presumed that all actions will be reactive, require relatively limited time for implementation, can be implemented immediately, and are taken in the aftermath of disaster. It may be beneficial, however, to take some preparedness actions, i.e., proactive measures, prior to disaster occurrence and before the random attributes of the disaster scenario are realized. Such actions may include changes that impact network structure, such as added capacity or redundancies, or that enhance opportunity for quick recovery, such as relocation of supplies for more immediate access in the event of disaster. These actions would be determined in the first stage. Program (R) can be modified for this purpose.

Although not the focus of this paper, one might extend this work to consider long-term recovery and reconstruction. Such considerations would require a dynamic network model where capacity is recaptured over time, and time-dependent arc-traversal times and capacities that reflect changes in network performance as postdisaster conditions improve. This is the subject of future research by the authors. Additionally, one might consider travel time as a function of link flows; however, the resulting formulation will likely be nonlinear.

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Appendix. Random Variate Generation
An approach developed by Chang, Tung, and Yang (1994) is applied herein to generate multivariate correlated random variates of arc capacities. This approach preserves the specified correlation structure among the random variables associated with a given scenario.

{Given expected capacity of each arc, correlation matrix R_c and marginal distribution F_a, $\forall a \in A$}

(1) Transform correlation matrix R_c to R_Y in the equivalent correlated standard normal space by a set of formulas $\rho^* = T_{ij} \times \rho_{ij}$;

(2) Construct an orthogonal transformation $R_Y = V\Lambda V^T$, where $\Lambda = diag\{\lambda_1, \lambda_2, \ldots, \lambda_n\}$, λ_i is the ith eigenvalue of R_Y;

(3) Generate independent standard normal random variates $Y = [y_1, y_2, \ldots, y_n]^T$;

(4) $Z = [z_1, z_2, \ldots, z_n]^T = V\Lambda^{1/2}Y$;

(5) $X = [x_1, x_2, \ldots, x_n]^T$ obtained by $x_i = F_i^{-1}((1/\sqrt{2\pi}) \int_{-\infty}^{z_i} e^{-z_i^2/2}\, dz_i)$.

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CORRECTION

In this article, "Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport" by Lichun Chen and Elise Miller-Hooks (first published in *Articles in Advance*, August 18, 2011, *Transportation Science*, DOI:10.1287/trsc.1110.0376), Equation (23) was corrected to read as follows:

$$Z - \sum_{a\in A}\sum_{k\in K} \Delta c_{ak}\pi_a\gamma_{ak} - \sum_{p\in P_w} D_w\pi_p y_p \le \sum_{a\in A} c_a\pi_a, \quad \forall\, \pi \in P_D$$