Hybrid Method of Recovery: Combining Topology and Optimization for Transportation Systems

Udit Bhatia, Ph.D., Aff.M.ASCE[1]; Lina Sela, Ph.D., A.M.ASCE[2]; and Auroop Ratan Ganguly, Ph.D., F.ASCE[3]

Abstract: Designing effective recovery strategies for damaged networks is important across built, human, and natural systems. Postperturbation network recovery has been motivated by two distinct philosophies, specifically, the use of centrality measures in complex networks versus network optimization measures. The hypothesis that hybrid approaches may offer complementary value and improve our understanding of recovery processes while informing real-world restoration strategies has not been systematically examined. This research shows that the two distinct network philosophies can be blended to form a hybrid recovery strategy that is more effective than either. Network centrality–based metrics tend to be intuitive and computationally efficient but remain static irrespective of the desired functionality or damage pattern. Optimization-based approaches, while usually less intuitive and more computationally expensive, can be dynamically adjusted. The proposed approach, based on edge recovery algorithms with edge importance informed by network flow and node attributes, outperforms recovery informed exclusively either by network centrality or network optimization. We find that optimization methods outperform centrality-based approaches for networks that are large enough for the power law to be manifested, but for treelike networks typically found at smaller scale, the two approaches are competitive and scenario specific. **DOI: 10.1061/(ASCE)IS.1943-555X.0000566.** © *2020 American Society of Civil Engineers.*

Author keywords: Recovery; Transportation network; Network science; Optimization; Cross entropy.

Introduction

Lifelines provide essential services to residents and businesses across geographic scales and help ensure the public's health and safety as well as economic security (Rinaldi et al. 2001). Energy, water, transportation, and communications represent the four primary lifelines, and comprise interdependent networked systems, such as the infrastructures that support power grids, water distribution or wastewater systems, multimodal transportation including railways, roads, airways, or waterways, and telephone, satellite, or Internet services. Natural, technological, and human-made catastrophes, including weather extremes and cyber-physical attacks, may severely disrupt the functioning of these lifeline infrastructure networks, thus causing loss of essential services. The corresponding impacts can be felt by rural and urban communities with cascading fallouts across cities, megalopolises, nations, regions, and indeed the entire globe (McNutt 2015). The ability to manage, adapt to, and mitigate the risks may determine the extent to which human society can benefit from globalization versus becoming increasingly vulnerable to large-scale failures. Probabilistic risk analysis, reliability engineering, operations research, and, in recent years, network science (Buldyrev et al. 2010; Clark et al. 2018; Ganin et al. 2016; Gao et al. 2016; Ouyang and Wang 2015) have demonstrated value in characterizing, designing, maintaining, and operating lifeline infrastructure networked systems (LINS). However, once disasters strike, intervention by emergency managers, stakeholders, and policymakers is imperative for the timely and efficient restoration of the essential services supported by LINS. One crucial knowledge gap in this context is the inability to provide systematic guidance for postdisruption recovery, let alone prepare such recovery plans in advance. While optimization approaches have demonstrated value in simulated or stylized settings and network science methods have shown initial promise with simulated or real-world networks (Bhatia et al. 2015; Clark et al. 2018; Ganin et al. 2016, 2017; Ulusan and Ergun 2018), principled strategies for recovery, especially those that can benefit from both, are still lacking.

Current efforts in infrastructure recovery (Ganin et al. 2016; NIAC 2010; Ouyang et al. 2012) include postdisaster maximum flow, connectivity recovery, identification of key components for resource allocation using network science–based approaches, and theoretical recovery frameworks for simulated networks (Bhatia et al. 2015; Clark et al. 2018; Ouyang et al. 2012). Existing infrastructure recovery methods either focus on network heuristics that prioritize restoration based on predefined measures or optimization methods that have been tested either on stylized or simulated networks (Ulusan and Ergun 2018). While centrality-based metrics tend to be intuitive and computationally efficient, they remain static irrespective of the desired essential functionality of networked infrastructures. Optimization-based approaches, while usually less intuitive and more computationally expensive, can potentially be better tailored to design objectives.

However, most real-world networks often differ from the stylized models and assessing the impact of disruptive events followed by recovery calls for a case-by-case assessment of the most efficient recovery strategies. For instance, an approach for joint restoration and modeling of interdependent infrastructures exemplified through interdependent gas and power systems at the county

[1]Assistant Professor, Dept. of Civil Engineering, Indian Institute of Technology, Gandhinagar, Palaj 382355, India; Civil and Environmental Engineering, Northeastern Univ., Boston 02115 (corresponding author). ORCID: https://orcid.org/0000-0002-0017-9085. Email: bhatia.u@iitgn.ac.in

[2]Assistant Professor, Dept. of Civil, Architectural and Environmental Engineering, Univ. of Texas at Austin, Austin, TX 78712. ORCID: https://orcid.org/0000-0002-5834-8451

[3]Professor, Dept. of Civil and Environmental Engineering, Northeastern Univ., Boston 02115. ORCID: https://orcid.org/0000-0002-4292-4856

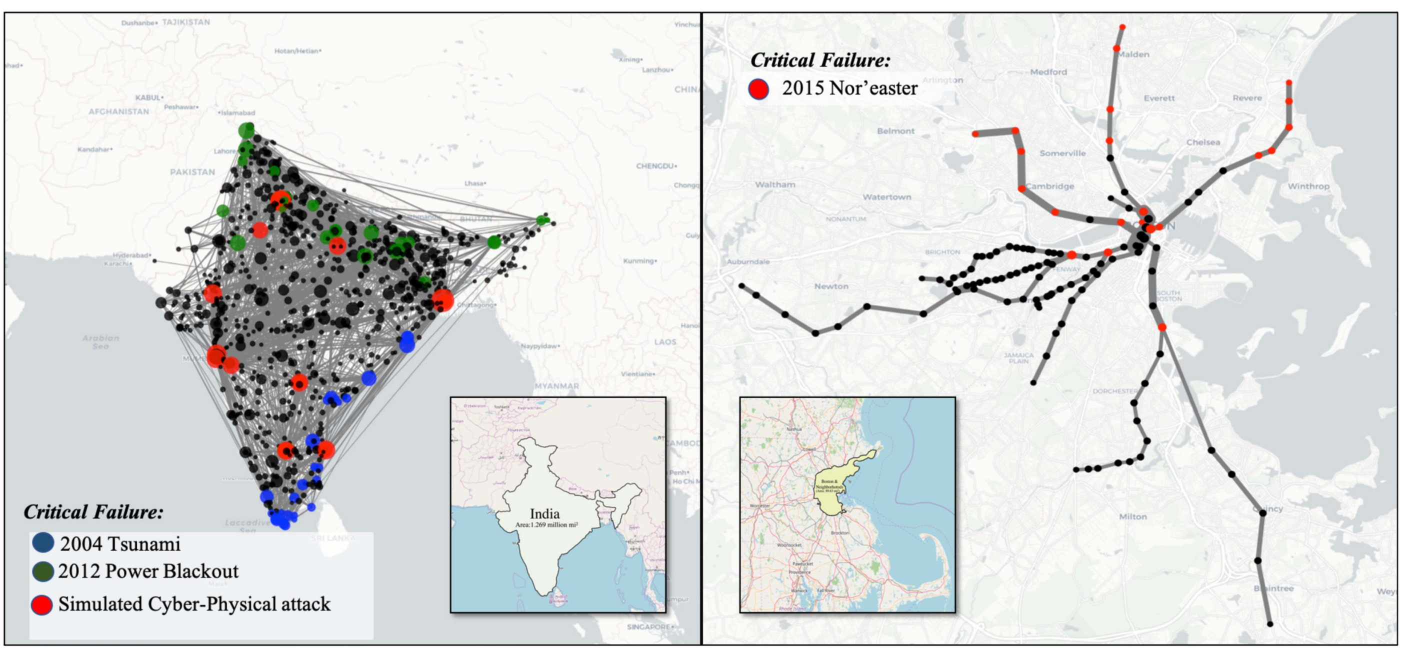
Note. This manuscript was submitted on March 25, 2019; approved on March 23, 2020; published online on June 1, 2020. Discussion period open until November 1, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Infrastructure Systems***, © ASCE, ISSN 1076-0342.

level impacted by a hurricane was proposed by Ouyang and Wang (2015). As noted, the proposed framework requires multiple components, including a hazard generation model, component fragility models, disaster-specific fragility curves, and system performance models, which may not be available for many real-world infrastructure systems that operate at large geographical scales and face a variety of potential threats. Also, infrastructure systems are often designed to meet multiple functionality criteria. When performance levels for infrastructure systems deteriorate after perturbation, these systems lose essential functionality from more than one standpoint (Ganguly et al. 2018).

To address the shortcomings, explore the complementary value network science–based approaches and optimization approaches to guide networked infrastructure recovery. While prior literature exists on network flow and optimization, there have been no previous attempts reported in the literature to blend network science with network optimization and translate such hybrid methods to recovery of lifeline infrastructure networks. We designed a strategy that blends network science and optimization to improve network recovery postperturbation and demonstrate it on two real-work networks. Specifically, we developed an edge recovery algorithm that blends network science–based heuristics including network centrality measures and optimization approaches including the greedy algorithm (Edmonds 1971; Krause et al. 2009) and cross-entropy (CE) algorithm (Rubinstein 1999) to inform recovery of real-world networks after disparate hazards. The greedy and CE algorithms that represent two distinct optimization approaches were selected to test the recovery performance when applied to networks following the treelike and power-law structure. The integrated approach enables us to design adjustable objective functions in which real-world constraints such as resources, recovery time, and a combination of nodes and edge failure can be included. We applied the model to two real-world transportation systems: the Indian Railways Network (IRN) and the Massachusetts Bay Transportation Authority (MBTA) system in the Greater Boston area. We modeled network disruptions inspired by real-life events. Then, we applied the proposed edge recovery algorithms to compare performance of various recovery strategies. The results may reveal important considerations for assessing proposals for disaster preparedness that in turn can help stakeholders act in advance to restore network functionality at faster rates.

Data

We generated models of two topologically distinct transportation systems operating at disparate scales. Specifically, we modeled the IRN and MBTA as networks, in which the nodes represent the transit stations. For IRN, a pair of nodes is considered connected by an edge if there is at least one origin and destination train between the pair. For MBTA, two nodes are considered connected if a pair of stations is connected by a direct train. We used two different network representations because both origin–destination (OD) and traffic flow data are frequently used in transportation for efficiency and resilience assessment studies depending on the data availability (Murray-Tuite 2006; Vugrin et al. 2014; Zhang et al. 2009). Here, we analyzed origin–destination data of passenger-carrying trains on the IRN. The network was constructed using publicly available data, which were cleaned and appropriately formatted prior to the analysis. The resulting IRN comprises 809 nodes (i.e., stations) with 7,066 edges (i.e., trains). We constructed the MBTA network by analyzing the open-source map available at the operator's website. Traffic flow data were obtained from MBTA (n.d.). The resulting MBTA network contains 121 nodes and 176 edges. Fig. 1(a) shows the resulting IRN and Fig. 1(b) shows the resulting MBTA networks. Traffic flow is a dynamic attribute of any transit network and it depends on multiple factors such as average delays, weather conditions, and the physical state of stations



(a) (b)

Fig. 1. Network visualization of transportation systems: (a) IRN; and (b) MBTA. Node size is proportional to the number of connections of each network. Critical failure nodes impacted by simulated cyber-physical hazards, 2004 Indian Ocean tsunami, and 2012 India blackouts are highlighted. Nodes impacted by 2013 snowstorms are shown in (b). Geographical maps in inset highlight the different scales at which these two transportation networks operate.

and tracks. However, these data sets are not publicly and widely available for either IRN or MBTA. Hence, we relied on open-source data sets for this study. The proposed approach can be straightforwardly updated given updated information of traffic flow conditions.

Critical Functionality of Lifelines

In the context of LINS, critical functionalities are defined as those functionalities that, if perturbed, can lead to serious societal emergency and crisis. Posthazard restoration efforts ought to restore these systems to the level of initial performance. Hence, we used state of critical functionality (SCF) as a performance measure, which is defined as the ratio of functionality at a given instance during the restoration process [instantaneous functionality (IF)] to a state of functionality before perturbation [target functionality (TF)]. Hence, $\text{SCF} = 1$ represents a fully functional system, whereas $\text{SCF} = 0$ represents the total loss of functionality. In a transportation context, the impact of perturbations unfolds in the form of loss or impairment of stations and/or linkages between these stations, which in turn results in loss of service such as delays, disruption of traffic flow, and loss of connectivity. In the present study, we used two different measures for SCF for the systems under consideration: (1) network connectivity assessed by measuring the size of the largest connected component (LCC) in a network, and (2) satisfying OD traffic demand measured as a total traffic flow in the LCC (Bhatia et al. 2015; Ganguly et al. 2018).

Perturbation and Recovery

To simulate perturbations on IRN, we considered three hazards inspired by real-life events: (1) the 2004 Indian Ocean tsunami (Grilli et al. 2007) that impacted stations and train tracks on the eastern coast of India; (2) cascading failure from the power grid based on the historically massive 2012 blackout (Lai et al. 2013); and (3) a cyber-physical attack scenario, in which transit stations are maliciously targeted based on traffic volume. In future sections, for brevity, we call these events tsunami, grid, and cyber-physical, respectively. The cyber-physical attacks are based on hypothetical scenarios, although motivated from real-world events such as the 2008 Mumbai terror attack (Azad and Gupta 2011; Bhatia et al. 2015). For MBTA, we considered a hazard inspired by the nor'easter of January 2015 (Rauber et al. 2016) that put up to 1 m of snow in various parts of New England. These hazards result in loss of impacted nodes and edges that are incident on these nodes. Loss of these components in turn results in reduced functionality because the system cannot sustain the TF (see Tables S1 and S2 for the list of affected stations by various hazards in the two networks).

Postperturbation system recovery entails strategic restoration of network components that are impacted by perturbation. When multiple components are lost, determining recovery sequences for restoration plays a crucial role in regaining the desired performance level and serviceability of the system (Ouyang et al. 2012). In this study, we focused on determining the optimal recovery sequence of edges, which results in the fastest recovery to predisaster functionality, i.e., minimizing the resilience loss. Resilience loss in this context is described as the mismatch between the targeted functionality and actual recovery curve and is a function of the intensity of the perturbation and duration of the recovery. Resilience loss is computed as the area between the TF and IF curves (Fig. 2). The definition of resilience loss used here is the direct application of the conceptual definition of the resilience triangle and a simple way to quantify resilience (Bruneau et al. 2003; Cimellaro et al. 2010).

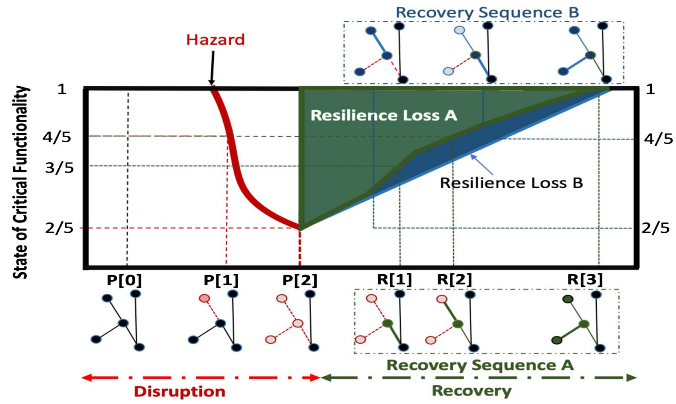


Fig. 2. Disruption and recovery process in representative network with five nodes and four edges. The efficiency of a strategy is measured in terms of resilience loss, which is the area bounded by the Y-axis and recovery curve traced by SCF. The strategy with the least resilience loss is comparatively more efficient.

For the representative network with five nodes and four edges, we measured SCF at time t as the ratio of the number of nodes at time t with respect to original number of nodes at $T = 0$. At time $P[0]$, $\text{SCF} = 1$ (prehazard). The edge shown marked by dotted lines was selected for removal at $t = P[1]$, resulting in isolation of the node shown in red, which sets SCF to $4/5$. At $P[2]$, another edge was removed, which further shrunk SCF to $2/5$. After the network was disrupted, the recovery process was initiated. With three edges removed, edge restoration can be determined in six ways. Out of six possible ways, we considered Recovery Sequences A and B. In Recovery Sequence A, when the green edge is restored at time $R[1]$, SCF changes from $2/4$ to $3/5$. The process of restoring one edge at a time is repeated until the network has $\text{SCF} = 1$ (prehazard state).

In this study, we propose network science and optimization approaches to solve the network recovery problem. The network science approach relies on network centrality measures to inform the recovery strategy. The optimization approach generates recovery strategies by directly minimizing resilience loss through making the locally best deterministic decision using the greedy approach and globally based heuristic decisions using the CE approach. Given the three perturbation scenarios considered previously, the network science and optimization approaches were tested, evaluated, and compared for the IRN and MBTA systems (see "Methods" for more detail).

Regardless of the approach, the outcome of the network and optimization-based approaches is a set of edges and a sequence in which the edges in the network should be restored. To assess the goodness of the recovery strategy, the edges and adjacent nodes are gradually restored and SCF is computed at each step. Specifically, recovery takes the following process:

1. TF is calculated at the prehazard state without perturbing nodes or edges.
2. IF is computed at the initial posthazard state for a given set of perturbed edges.
3. Given a set and a sequence of edges that should be restored, at each step:
   a. The next edge in the prioritization sequence and its adjacent nodes is restored, establishing flow between a pair of nodes connected by the edge. This increases the size of the largest connected component and enables traffic flow across the network.

b. IF is recalculated.
c. SCF is calculated.

Methods

Network Science–Based Recovery Approaches

We built on network centrality measures to generate prioritization sequences for perturbed systems; specifically, we relied on degree, closeness, betweenness, and eigenvector centrality measures (Clark et al. 2018). Different centrality indexes measure distinctive aspects related to a position of nodes within a network. For example, betweenness centrality describes the importance of a node as a connector between different parts of the network. Alternatively, closeness centrality measures the proximity of a node to all other nodes. Nodes with high closeness centrality values can rapidly affect other nodes and vice versa. Degree centrality is a measure of the number of connections originating (or terminating) at a node, whereas eigenvector centrality is a measure of influence of the node. A high eigenvector centrality means the node is connected to many more nodes that have a high degree. Similarly, edge betweenness centrality is defined as the number of the shortest paths that go through an edge in a network.

We considered two performance metrics, where the resilience is a function of: (1) network connectivity and (2) the origin–destination demand that can be satisfied. For Function 1, we considered a topology-based centrality measure, whereas for Function 2 a weighted version of network centrality was used, where weight of an edge represents the number of trains scheduled to operate on a given edge. Specifically, we used weighted degree (sum of weights incident upon a node), weighted closeness centrality (measuring proximity of a node while using inverse of weights to find the least costly path among all nodes), and weighted edge betweenness centrality based on the algorithm proposed by Newman (2002).

Intuitively, an edge connecting two important nodes should act like a bridge between two parts of a network. Hence, removal (restoration) of such an edge could result in faster destruction (recovery) of the system. Hence, in addition to edge betweenness centrality, we also accounted for the importance of a pair of nodes between which an edge is positioned. We computed averages of closeness, eigenvector, and degree centrality for each pair of nodes in the network, and centrality-based scores were used as measures to establish the edge prioritization sequence. The higher the centrality-based score, the higher the prioritization assigned to an edge during the recovery process.

Optimization-Based Recovery Approaches

The greedy and CE algorithms represent two distinct optimization approaches were selected to test the recovery performance when applied to networks following the treelike and power-law structure. The greedy algorithm belongs to a class of deterministic optimization approaches that make locally best decisions given available information. The CE algorithm belongs to a class of heuristic simulation-based approaches that make global decisions by generating many realizations of probable solutions. In both approaches, the goal is to find a feasible solution that satisfies all the constraints while optimizing (i.e., maximizing in our setting) a predefined objective function. Both approaches have the advantage over the network-based method because of their ability to model the objectives (and constraints) of the decision maker and incorporate these in the optimization process. Both the greedy and CE algorithms require having a way to evaluate system performance, e.g., through sampling or model simulations. The methods differ, however, in their solution approach. The greedy algorithm is a sequential deterministic algorithm that selects in each step the best local decision and continues to the next best local decision until all decisions are covered and the final solution is achieved. Thus, the final solution constitutes a sequence of local best decisions. On the contrary, the CE algorithm is a stochastic global algorithm that optimizes the underlying probability of the solutions instead of directly optimizing the decision variables. Thus, all the decisions for the entire planning horizon are made at once. The greedy algorithm has the advantages of being (1) computationally efficient because of its deterministic nature and requiring evaluation of the system's response to each decision one step at a time (and not the combinations of many decisions over the entire planning horizon) and (2) adaptive to the changing conditions through sequential decision-making, which allows adjusting the decision strategy once new information is revealed. The CE has the advantages of (1) making globally optimal decisions by considering the entire planning horizon and not being affected by local properties of the network and (2) providing near-optimal solutions when using tuned parameters.

The greedy algorithm has the disadvantages of being trapped by local optimums and thus not reaching globally good solutions. The CE algorithm relies on a large number of simulations, which typically makes it computationally intense especially for large systems. The main drawback of both approaches is that they do not provide performance guarantees on the quality of the solution. However, they have been highly successful for applications in a variety of computer science and optimization problems and empirically result in good-quality solutions (Kapur and Kesavan 1992; Moher 1993).

To formulate the recovery problem, we defined the recovered edges as the decision variables. Our goal was to achieve a fast recovery to the predisaster functionality, i.e., minimize resilience loss. Thus, we defined the objective function as the area under the resilience curve that we wish to minimize. We considered two performance metrics, where the resilience is a function of network connectivity and the origin–destination demand that can be satisfied. The outcome of the optimization approach, either greedy algorithm or CE, would provide the sequence of the edges that should be restored to achieve the minimum resilience loss.

Intuitively, the greedy algorithm approach is to iteratively select the solution (edge) that contributes the most to the network functionality at the current stage, until all edges are restored and the network regains its full functionality. The main steps of the greedy approach are outlined in Table S3 and a full description can be found in Rubinstein (1999). The greedy algorithm has been widely studied in the context of submodular function optimization and combinatorial optimization in a wide range of applications, e.g., sensor placement and scheduling (Krause et al. 2008). In the case where the objective function is monotone submodular (Topkis 1978), the greedy approximation can provide performance guarantees. For the recovery problem, this means that as the number of recovered edges increases, the marginal value of system functionality decreases. This assumption does not hold in our case and we cannot provide performance guarantees. However, in practice, the greedy algorithm still shows better performance than the theoretical guarantees.

The recovery problem was also solved using the CE method for combinatorial optimization (Rubinstein 1999). The CE algorithm is a heuristic search technique that utilizes probabilities of outcomes of the decision variables instead of the actual values. Intuitively, the CE algorithm associates probabilities with the decision variables and the goal is to find the optimal probability distributions for

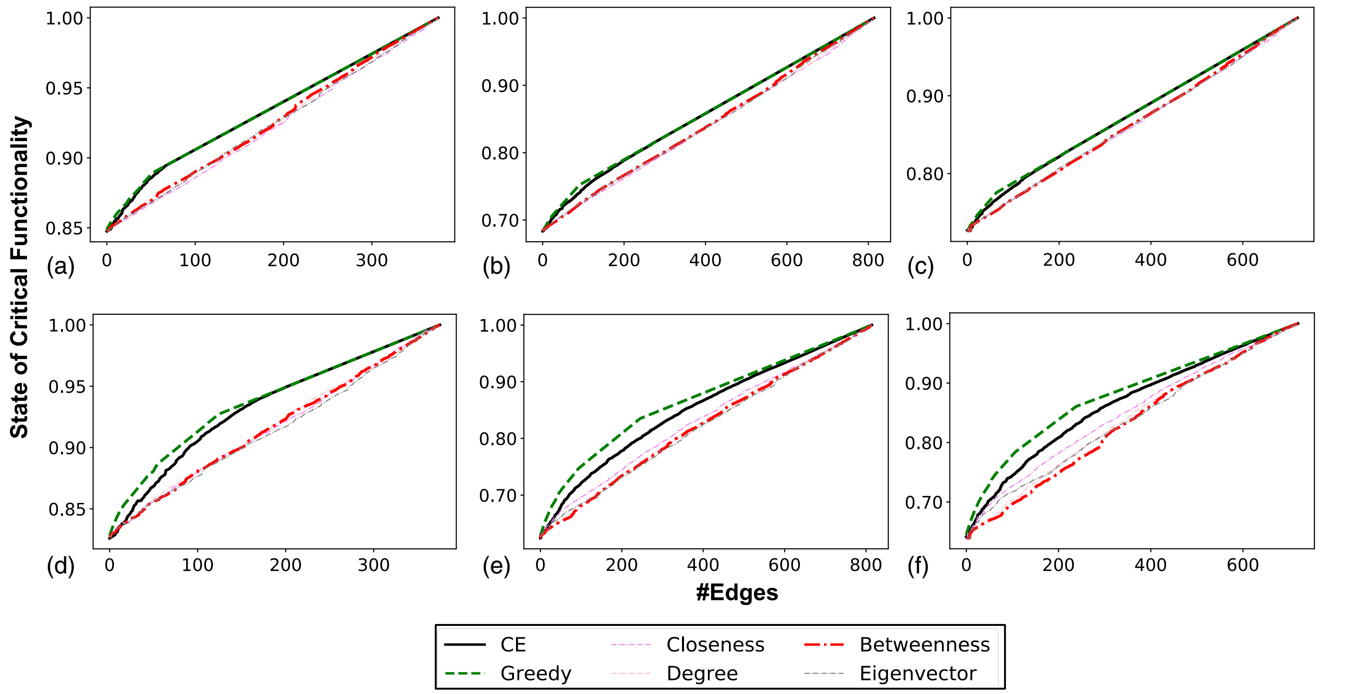


Fig. 3. Recovery of Indian Railways Network after three hazards: (a and d) simulation inspired by 2004 Indian Ocean tsunami; (b and e) scenario based on a cascade from the power grid; and (c and f) a cyber or cyber-physical attack scenario. Five approaches (two optimization based and three network science based) were used to generate edge prioritization sequences for perturbed sequences; the two optimization approaches and one network-based approach (edge betweenness centrality) are shown in solid lines. In all three cases and for both performance measures, optimization-based recovery approaches are more efficient than network centrality–based approaches, on average, by 9% in terms of resilience loss (area between Y-axis and recovery curve). Table 1 summarizes the resilience loss calculated for the three hazards and two performance measures.

the decision variables. For example, $p(x_{i,t})$ represents the probability of recovering edge i at time t, starting with a random probability. The CE algorithm will converge when the probabilities are close to $p(x_{i,t})$, representing that edge i is recovered at time t and is 0 otherwise. To find the optimal probabilities, the CE algorithm relies on a two-stage iterative process: (1) generating potential solutions from the sampling probability, and (2) updating of the parameters of the sampling probabilities to find better solutions by minimizing the Kullback-Leibler distance (Kullback and Leibler 1951) between the sampling probability and the theoretical optimal probability. The CE algorithm has three parameters that control its performance, including sample size, which defines the number of samples in each iteration; the elite sample percentage, which defines the best set of solutions used for updating the parameters of the sampling probability; and a smoothing parameter, which prevents premature convergence. The main steps of the CE approach are outlined in Table S3 and a detailed description can be found in Rubinstein (1999).

Results

We measured efficiency of each recovery strategy by computing the corresponding resilience loss, as defined previously (Fig. 2). A lower area means higher efficiency because it represents the mismatch between the actual functionality during recovery and the targeted functionality at which the system was operating before perturbation.

We used connectivity and traffic volume as the two performance measures for SCF. We simulated three hazard scenarios for the IRN and MBTA networks under consideration (see "Methods"). For IRN, Fig. 3 shows the simulation results of applying the network science and optimization recovery strategies and Table 1 summarizes the resilience loss under each hazard scenario and recovery strategy. For IRN, SCF dropped by 14% and 16%; cascades of failure from the power grid based on 2012 blackout resulted in SCF loss of 30% and 35%; whereas the simulated cyber-physical attack caused loss of 27% and 35% of SCF in terms of connectivity and traffic volume, respectively. To restore the SCF of the perturbed network to TF, we used edge prioritization sequences determined from network science–based and optimization-based approaches. We found that for IRN, the optimization-based approach results in better performance than network science–based approaches. On average, optimization strategies are 12% and 40% more efficient when compared with centrality-based strategies for both connectivity recovery and traffic flow recovery, respectively (Fig. 3 and Table 1).

For MBTA, Fig. 4 and Table 2 show the performance results and resilience loss, respectively, under each hazard scenario and recovery strategy. Results show that the 2015 nor'easter scenario exhibits disproportionately adverse impacts on SCF as removal of 9% of the edges (17/176) resulted in 80% loss of SCF in terms of connectivity as well as traffic volume. Contrary to our finding for IRN, we observed that the network science–based recovery approach, specifically edge betweenness centrality, outperformed the greedy algorithm approach by 41%, whereas efficiency from the CE algorithm was comparable to the edge betweenness centrality (Fig. 3).

On the other hand, we found that for MBTA, which approaches a treelike network topology, approaches such as the greedy algorithm that tend to maximize instant or short-term restoration of functionality may turn out to be myopic and inefficient at the system level over the lifetime recovery process (Fig. 4). Specifically, the

Table 1. Recovery scores for Indian Railways Network

	Hazards on IRN					
	Tsunami		Grid		Cyber-physical attack	
	Edges recovered					
	376		815		720	
Recovery algorithm	Connectivity recovery	Traffic flow recovery	Connectivity recovery	Traffic flow recovery	Connectivity recovery	Traffic flow recovery
Greedy optimization	26.60	25.15	116.92	108.73	91.27	87.70
Closeness	29.79	34.47	128.65	150.98	99.75	128.87
Degree	29.24	34.18	128.69	247.59	100.06	126.24
Betweenness	29.20	33.93	127.65	147.76	99.63	126.34
Eigenvector	29.88	34.63	128.50	150.52	100.13	130.42
Cross entropy	26.75	26.60	118.01	120.93	92.02	98.80

Note: Resilience loss is measured as the area between the Y-axis and state of resilience curve, traced by each strategy curve during recovery process. A lower area means a more efficient recovery strategy.

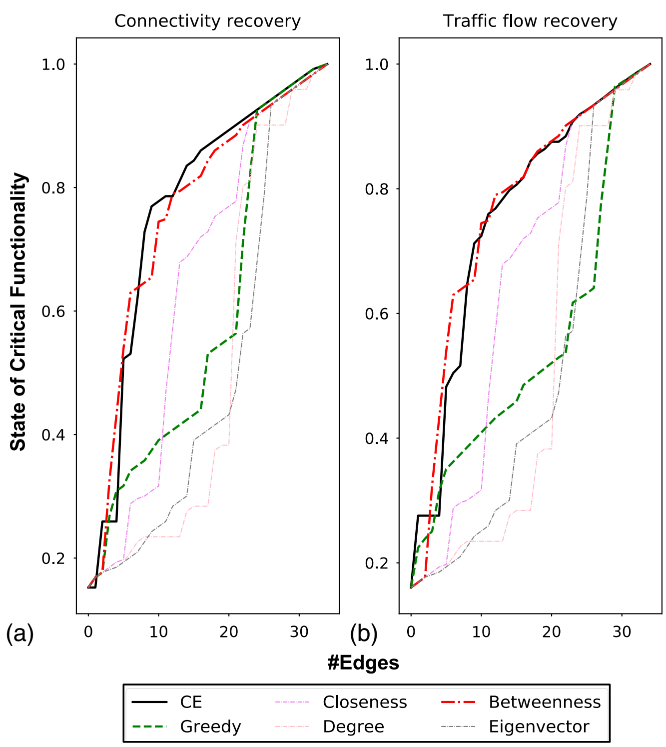


Fig. 4. Recovery of MBTA after 2015 nor'easter. Five approaches (two optimization based and three network science based) were used to generate edge prioritization sequences for perturbed sequences; the two optimization approaches and one network-based approach (edge betweenness centrality) are shown in solid lines. (a) Recovery of SCF in terms of network connectivity shows that network-based edge betweenness performs as well as CE optimization, and both these approaches outperform the greedy algorithm by nearly 41% in terms of efficiency; and (b) similar insights are obtained when traffic volume is used to measure SCF. Table 2 summarizes the resilience loss calculated for the two performance measures.

Table 2. Recovery scores for Boston's MBTA

	2015 nor'easter, Boston	
	Edges recovered	
	35	
Recovery algorithm	Connectivity recovery	Traffic flow recovery
Greedy optimization	17.26	15.95
Closeness	11.16	11.26
Degree	14.30	13.85
Betweenness	10.18	9.77
Eigenvector	16.8	17.84
Cross entropy	10.31	9.74

Note: Resilience loss is measured as the area between the Y-axis and state of resilience curve, traced by each strategy curve during recovery process. A lower area means a more efficient recovery strategy.

network-based recovery approach outperformed the optimization-based greedy algorithm by 41% and 38% for network connectivity recovery and traffic flow recovery, respectively. The edge centrality–based recovery was marginally better than CE. Both CE and edge centrality outperform the greedy algorithm by 40% (Table 2). This holds true for both connectivity recovery and traffic flow recovery. Because the CE algorithm is heuristic in nature, to ensure that our results are robust to the choice of parameters, we performed many CE optimizations using three different choices of parameters and we observed that efficiency scores thus obtained were insensitive to parameter choice for both objective functions (Fig. S1). Comparison of the CE and greedy algorithm approaches at various time steps during the recovery process is shown in Fig. S2.

To understand the relationship between topological features of the network and recovery scores, we plotted degree distribution and weighted degree distribution of the network. In addition, we also measured network assortative to measure the similarity of connections in the networks with respect to node degree. We found that IRN follows the power-law distribution in degree as well as weighted degree distribution. That is, degree distribution follows the form

$$P(k) \sim k^{-\gamma} \quad (1)$$

where $P(k)$ = fraction of nodes in the network that have k connections; and $\gamma = 1.84$ (p-value < 0.05, Student t-test). As shown in prior research (Bhatia et al. 2015; Clark et al. 2018), for networks exhibiting a power law in their degree distribution, centrality measures are often correlated with degree of nodes and hence generating node restoration sequences using network centrality attributes often yield high recovery efficiency. However, this intuition may not hold true in the case of edge recovery. We found that the degree assortativity coefficient for this network is 0.062, which means there is no preference of a network node of high degree to attach to other high degree nodes (Newman 2002). As a result, ranking edges based on the pair of attributes of adjacent nodes does not yield the most efficient recovery trajectories. On other hand, MBTA exhibits a treelike structure (Latora and Marchiori 2002) with 80% of nodes having degrees in the range of 1 and 3 [Figs. 1(b) and 5 (right)]. For localized damage on treelike networks such as MBTA, the greedy algorithm approach fails to identify the systemwide optimal just by maximizing functionality at each step because attributes of edges in a treelike network are similar. Edges with higher edge betweenness (Lu and Zhang 2013) tend to bridge the broken network at a faster rate, therefore exhibiting high efficiency. Recovery scores from various recovery strategies for both networks are summarized in Table 1.

Conclusion

Postperturbation network recovery strategies have been motivated by two distinct philosophies, specifically, centrality measures in complex networks versus network optimization including entropy measures. Here we showed that they may be blended to offer complementary value for the recovery of networked infrastructure systems (Figs. 3 and 4; Table 1). We designed a strategy that blends network science and optimization to improve network recovery postperturbation and demonstrated on two real-world networks, specifically, the IRN and the MBTA network. Our hybrid approach shows that the optimal algorithm at each recovery step may be situation specific and allowing an automated way to choose between network science versus network optimization methods may result in gains of efficiency by anywhere from about 10% to about 40% for both network connectivity and traffic flow recovery. Furthermore, the performance can be mapped to the network attributes. Thus, optimization approaches work better for the IRN, which approaches scale-free network attributes, while network centrality approaches work better for MBTA, which approaches a planar network. However, the performance at any specific recovery step may be dependent on the characteristics of the current attribute of the damaged network.

Recovery strategies may need to handle trade-offs between multiple and potentially disparate essential services they were designed to provide. Recovery approaches need to adjust to the current state of a lifeline infrastructure network rather than being exclusively guided by the topology of a system prior to loss of functionality. The network topology and flow attributes of a specific lifeline system determine the extent to which systematic or dynamic approaches may improve recovery of any specific lifeline network or generalize to other lifelines. Recovery strategies that dynamically consider multiple essential services and account for both network and flow attributes tend to be more reliable and generalize better across systems. Infrastructure and lifeline recovery strategies have traditionally tended to be bottom-up, where component-specific and granular information are used where available, in the absence of which relatively ad hoc strategies become the default choice. The top-down approaches proposed here offer a way for infrastructure owners and operators to make recovery strategies that may be optimal at the overall system level functionality.

We note that the optimal algorithm at each recovery step may be situation specific and allowing an automated way to choose between network science versus network optimization methods may result in gains of efficiency by anywhere from about 10% to about 40% for both network connectivity and traffic flow recovery. Specifically, we note the following:

- IRN: Optimization-based approaches are 9% and 25% more efficient than network centrality–based approaches for network connectivity recovery and traffic flow recovery, respectively. Optimization-based approaches (both the greedy algorithm and CE) are better at all recovery steps as well are more efficient in terms of resilience loss. This holds true for all three scenarios: tsunami, power grid cascade, and simulated cyber-physical attack.
- MBTA: The network-based recovery approach outperforms the optimization-based greedy algorithm by 41% and 38% for network connectivity recovery and traffic flow recovery, respectively. The network centrality approach is marginally better than CE. Both CE and network centrality outperform the greedy algorithm by 40%. This holds true for both connectivity recovery and traffic flow recovery.
- Furthermore, the performance can be broadly mapped to the network attributes. Thus, optimization approaches work better for the IRN, which exhibits a power law in the degree distribution, while network centrality approaches work better for MBTA, which approaches a planar network. However, the performance at any specific recovery step may be dependent on the characteristics of the current attribute of the damaged network. Thus, the hybrid approach that selects the best performing approach at the recovery time steps would appear to be the best suited.

While future research may need to balance the traditional bottom-up approaches with emerging top-down methodologies, none of these address data limitations and information gaps on their own. Thus, the proposed approaches need to make assumptions about resource constraints, recovery time, and fragility at component levels. However, while these assumptions do limit the validity of the conclusions in a data-limited study, they also point to what new data may add value to the analysis and help improve the credibility of the results. Validation of the model results proposed here requires information on the extent of damage, structural redundancies, and inclusion of social and human factors, including time-varying network attributes. Real-time data monitoring and data ingestion in the proposed models could be a valuable area of research to explore in the future.

In the present case, the problem formulation was driven by data availability and transportation networks can be modeled on an individual link level or origin–destination level. Our application is a bit limited because we relied on publicly available data sets; however, we demonstrated that our approach is general and can be applied to both types of network models. Interesting future extensions are to compare the outcomes and insights of recovery strategies for the same transit networks having different representation. We have clearly discussed these caveats in the "Conclusion" section. Infrastructure owners and operators may have direct access to component-specific data about resources and vulnerabilities that could augment the methodologies proposed and demonstrated here.

One final caveat is that the optimization algorithms require additional information about the desired performance function which is not always available, or different stakeholders are expected have different objective functions. Additionally, the performance of heuristic algorithms, such as CE, is dependent on parameter selection and thus requires off-line parameter tuning. This process is computationally expensive and there are no proven guidelines on the best parameter selection.

Large-scale disasters have revealed that decision makers often struggle to identify or determine key components and interdependency relationships in infrastructure systems, optimal resource allocation to increase resilience or reduce risk, and optimal response plans. Although interest has increased in policies that enhance resilience of these systems, few analytic tools are available to guide new investments in achieving resilience goals. Our analysis offers several meaningful inferences to be made that may have important implications for resilience policy for systems operating at various jurisdictional and geographical levels. Future research needs to include underlying dynamic behavior of networks as well as understand the dependence across systems in the assessment of optimal recovery trajectories of the lifeline infrastructure networked systems that shape modern-day societies.

Acknowledgments

This work was supported in part by the Civil and Environmental Engineering Department, Sustainability and Data Sciences Laboratory, Northeastern University. The work of U. Bhatia and A. R. Ganguly was supported by four National Science Foundation Projects, including NSF BIG DATA under Grant No. 1447587, NSF Expedition in Computing under Grant No. 1029711, NSF CyberSEES under Grant No. 1442728, and NSF CRISP type II under Grant No. 1735505.

Supplemental Material

Figs. S1 and S2 and Tables S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

References

Azad, S., and A. Gupta. 2011. "A quantitative assessment on 26/11 Mumbai attack using social network analysis." *J. Terrorism Res.* 2 (2): 4–14. https://doi.org/10.15664/jtr.187.

Bhatia, U., D. Kumar, E. Kodra, and A. R. Ganguly. 2015. "Network science based quantification of resilience demonstrated on the Indian railways network." *PLoS One* 10 (11): e0141890. https://doi.org/10.1371/journal.pone.0141890.

Bruneau, M., S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O'Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. von Winterfeldt. 2003. "A framework to quantitatively assess and enhance the seismic resilience of communities." *Earthquake Spectra* 19 (4): 733–752. https://doi.org/10.1193/1.1623497.

Buldyrev, S. V., R. Parshani, G. Paul, H. E. Stanley, and S. Havlin. 2010. "Catastrophic cascade of failures in interdependent networks." *Nature* 464 (7291): 1025–1028. https://doi.org/10.1038/nature08932.

Cimellaro, G. P., A. M. Reinhorn, and M. Bruneau. 2010. "Framework for analytical quantification of disaster resilience." *Eng. Struct.* 32 (11): 3639–3649. https://doi.org/10.1016/j.engstruct.2010.08.008.

Clark, K. L., U. Bhatia, E. A. Kodra, and A. R. Ganguly. 2018. "Resilience of the US national airspace system airport network." *IEEE Trans. Intell. Transp. Syst.* 19(12): 3785–3794. https://doi.org/10.1109/TITS.2017.2784391.

Edmonds, J. 1971. "Matroids and the greedy algorithm." *Math. Program.* 1 (1): 127–136. https://doi.org/10.1007/BF01584082.

Ganguly, A. R., U. Bhatia, S. E. Flynn, U. Bhatia, and S. E. Flynn. 2018. *Critical infrastructures resilience: Policy and engineering principles*. New York: Routledge.

Ganin, A. A., M. Kitsak, D. Marchese, J. M. Keisler, T. Seager, and I. Linkov. 2017. "Resilience and efficiency in transportation networks." *Sci. Adv.* 3 (12): e1701079. https://doi.org/10.1126/sciadv.1701079.

Ganin, A. A., E. Massaro, A. Gutfraind, N. Steen, J. M. Keisler, A. Kott, R. Mangoubi, and I. Linkov. 2016. "Operational resilience: Concepts, design and analysis." *Sci. Rep.* 6 (1): 1–12. https://doi.org/10.1038/srep19540.

Gao, J., B. Barzel, and A.-L. Barabási. 2016. "Universal resilience patterns in complex networks." *Nature* 530 (7590): 307–312. https://doi.org/10.1038/nature16948.

Grilli, S. T., M. Ioualalen, J. Asavanant, F. Shi, J. T. Kirby, and P. Watts. 2007. "Source constraints and model simulation of the December 26, 2004, Indian Ocean tsunami." *J. Waterw. Port Coastal Ocean Eng.* 133 (6): 414–428. https://doi.org/10.1061/(ASCE)0733-950X(2007)133:6(414).

Kapur, J. N., and H. K. Kesavan. 1992. "Entropy optimization principles and their applications." In *Entropy and energy dissipation in water resources, Vol. 9 of Water Science and Technology Library*, edited by V. P. Singh and M. Fiorentino, 3–20. Dordrecht, Netherlands: Springer.

Krause, A., J. Leskovec, C. Guestrin, J. Vanbriesen, M. Asce, and C. Faloutsos. 2009. "Efficient sensor placement optimization for securing large water distribution." *J. Water Resour. Plann. Manage.* 134 (6): 516–526. https://doi.org/10.1061/(ASCE)0733-9496(2008)134:6(516).

Krause, A., A. Singh, and C. Guestrin. 2008. "Near-optimal sensor placements in Gaussian processes: Theory, efficient algorithms and empirical studies." *J. Mach. Learn. Res.* 9 (Feb): 235–284.

Kullback, S., and R. A. Leibler. 1951. "On information and sufficiency." *Ann. Math. Stat.* 22 (1): 79–86. https://doi.org/10.1214/aoms/1177729694.

Lai, L. L., H. T. Zhang, C. S. Lai, F. Y. Xu, and S. Mishra. 2013. "Investigation on July 2012 Indian blackout." In Vol. 1 of *Proc., 2013 Int. Conf. on Machine Learning and Cybernetics*, 92–97. New York: IEEE. https://doi.org/10.1109/ICMLC.2013.6890450.

Latora, V., and M. Marchiori. 2002. "Is the Boston subway a small-world network?" *Physica A: Stat. Mech.* 314 (1): 109–113. https://doi.org/10.1016/S0378-4371(02)01089-0.

Lu, L., and M. Zhang. 2013. "Edge betweenness centrality." In *Encyclopedia of systems biology*, edited by W. Dubitzky, O. Wolkenhauer, K.-H. Cho, and H. Yokota, 647–648. New York: Springer.

MBTA (Massachusetts Bay Transportation Authority). n.d. "Schedules and maps." Accessed July 15, 2018. https://www.mbta.com/schedules/.

McNutt, M. 2015. "Preparing for the next Katrina." *Science* 349 (6251): 905s. https://doi.org/10.1126/science.aad2209.

Moher, M. 1993. "Decoding via cross-entropy minimization." In Vol. 2 of *Proc., GLOBECOM '93. IEEE Global Telecommunications Conf.*, 809–813. New York: IEEE. https://doi.org/10.1109/GLOCOM.1993.318192.

Murray-Tuite, P. M. 2006. "A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions." In *Proc., 38th Conf. on Winter Simulation, WSC '06, Winter Simulation Conf.*, 1398–1405. New York: IEEE. https://doi.org/10.1109/WSC.2006.323240.

Newman, M. E. J. 2002. "Assortative mixing in networks." *Phys. Rev. Lett.* 89 (20): 208701. https://doi.org/10.1103/PhysRevLett.89.208701.

NIAC (National Infrastructure Advisory Council). 2010. *A framework for establishing critical infrastructure resilience goals*. Final Report and Recommendations by the Council. US Dept. of Homeland Security.

Ouyang, M., L. Dueñas-Osorio, and X. Min. 2012. "A three-stage resilience analysis framework for urban infrastructure systems." *Struct. Saf.* 36–37 (May–Jun): 23–31. https://doi.org/10.1016/j.strusafe.2011.12.004.

Ouyang, M., and Z. Wang. 2015. "Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis." *Reliab. Eng. Syst. Saf.* 141 (Sep): 74–82. https://doi.org/10.1016/j.ress.2015.03.011.

Rauber, R. M., S. M. Ellis, J. Vivekanandan, J. Stith, W.-C. Lee, G. M. McFarquhar, B. F. Jewett, and A. Janiszeski. 2016. "Finescale structure of a snowstorm over the northeastern United States: A first look at high-resolution HIAPER cloud radar observations." *Bull. Am. Meteorol. Soc.* 98 (2): 253–269. https://doi.org/10.1175/BAMS-D-15-00180.1.

Rinaldi, S. M., J. P. Peerenboom, and T. K. Kelly. 2001. "Identifying, understanding, and analyzing critical infrastructure interdependencies."

IEEE Control Syst. Mag. 21 (6): 11–25. https://doi.org/10.1109/37.969131.

Rubinstein, R. 1999. "The cross-entropy method for combinatorial and continuous optimization." *Methodol. Comput. Appl. Probability* 1 (2): 127–190. https://doi.org/10.1023/A:1010091220143.

Topkis, D. M. 1978. "Minimizing a submodular function on a lattice." *Oper. Res.* 26 (2): 305–321. https://doi.org/10.1287/opre.26.2.305.

Ulusan, A., and O. Ergun. 2018. "Restoration of services in disrupted infrastructure systems: A network science approach." *PLoS One* 13 (2): e0192272. https://doi.org/10.1371/journal.pone.0192272.

Vugrin, E. D., M. A. Turnquist, and N. J. K. Brown. 2014. "Optimal recovery sequencing for enhanced resilience and service restoration in transportation networks." *Int. J. Crit. Infrastruct.* 10 (3–4): 218–246. https://doi.org/10.1504/IJCIS.2014.066356.

Zhang, L., Y. Wen, and M. Jin. 2009. *The framework for calculating the measure of resilience for intermodal transportation systems*. Denver: National Center for Intermodal Transportation.