Seismic Resilience of a Rail-Truck Intermodal Freight Network

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ABSTRACT: This study introduces a framework for seismic resilience assessment of rail-truck intermodal freight networks. Although highways constitute the leading mode of freight transport in terms of value and tonnage, railroads primarily support efficient long-haul transport, leading the way in terms of ton-miles of freight traffic. Disruptions to rail and highway infrastructure from hazards such as earthquakes can have distinct impacts on intermodal transport of goods at various spatial and temporal scales. In this study, a framework is proposed for evaluating the temporal evolution of intermodal network resilience, building on past research on performance of intermodal freight networks under disruption. The generic framework is capable of accounting for various costs associated with transporting a freight shipment from its designated origin to its destination. In this study, two simple applications of the framework are shown, in terms of the value weighted connectivity and the value weighted inverse travel distance, the formulations for which are explained in relevant sections. The proposed framework facilitates the estimation of quantities such as overall network throughput at various stages of recovery, which can be used by economists to study the corresponding effects on local and nationwide economy.

Railroads and highways are the leading carriers of freight traffic in the United States, forming key components of the largest freight transportation network in the world (Bureau of Transportation Statistics 2012). Damaging natural and anthropogenic hazards pose the threat of disruption and consequent loss of functionality to the infrastructure links, resulting in widespread consequences on the local as well as nationwide economy. Although such hazards typically affect a small part of the network, its consequences may be observed on a much larger scale. In this paper, the methodological framework to evaluate seismic resilience of a rail-truck intermodal network is proposed, leveraging key input models to simulate a post-hazard disruption scenario and input data from relevant sources to study the economic consequences. This framework is illustrated using a case study with a scenario event from the New Madrid seismic zone and its effects on the nearby intermodal network of Memphis, TN and surrounding regions. Using a multi-scale approach to network modeling, the resilience can be studied both on a local as well as nationwide scale.

Resilience with respect to an infrastructure system refers to its ability to react to stresses and recover functionality in a robust and efficient manner. The concept of resilience thus encompasses several aspects, ranging from inherent robustness and redundancy of the system to pre-event preparedness actions and post-event recovery actions. Bruneau et al. (2003) define resilience from a community perspective in terms of reduced probability of failure, reduced consequences and reduced recovery time. This definition is adapted by Lounis and McAllister (2016) as the ability of a system to maintain acceptable levels of functionality, accounting for the relevant uncertainties in pre-event conditions, post event loss of functionality and consequent time to recovery. The metrics used to define hazard resilience of infrastructure systems should be able to take into account the structural capacity of their components to resist physical damage, appropriate functions relating damage to functionality and time to recovery, while considering inherent redundancies in the system. Ip and Wang (2011) proposed a resilience metric for transportation networks as the weighted sum of the reliability of all edge-independent routes connecting an origin-destination pair, summed across all such pairs of interest. With respect to freight networks in particular, Miller-Hooks et al. (2012) provided a definition of network resilience as the ratio of pre-event demand satisfied post-event, with the capability to account for constraints in budget and time in addition to pre-disaster preparedness actions.

Intermodal networks are defined as those which have at least two or more different transportation modes linked end-to-end for moving freight (Southworth and Peterson 2000). Highways, railroads and port facilities typically are the lead actors in intermodal freight transport, with truck and rail participating primarily in domestic transport of goods. In the recent past, several studies on optimal routing and traffic assignment in rail and intermodal freight transportation networks have been conducted (Uddin and Huynh 2015, Miller-Hooks et al. 2009, Hwang and Ouyang 2014). In addition, there has been considerable interest in the performance of rail and intermodal freight networks under disruption (Miller-Hooks et al. 2012, Dong et al. 2015, Uddin and Huynh 2016). These studies typically consider the effect of synthetic failure scenarios of intermodal stations or network links selected either strategically or at random, without accounting for the physical vulnerability of constituent components of the intermodal system. As a result, there is a need to account for physical damage state probabilities, coupled with probabilities of network edge closure and their corresponding restoration trajectories, into a time-evolving resilience framework.

This study uses a multi-scale network modeling approach to evaluate the resilience of the railway network against a scenario New Madrid earthquake originating near Memphis, TN, a major freight hub in central and southeastern US. The multi-scale approach allows for exploring the effects of network disruption both at a regional and a nationwide scale. The multi-scale modeling approach is an adaptation of the "network of networks" approach (Sela et al. 2017), where networks of varying resolutions are applied at different scales depending on the demands of the problem, while being connected.

1. NETWORK DETAILS

The overall intermodal network model consists of three distinct component networks; the high-resolution regional railroad network of Shelby County, TN (Int1), the high-resolution regional highway network of Shelby County, TN (Int2) and a simplified representation of the nationwide railway network (Int3). The topological characteristics of the three individual networks are described in the following subsections. A network is represented by a set of vertices (or nodes) and a set of edges (or links) connecting them. Each of these networks is represented using an adjacency matrix, a $n \times n$ binary matrix (where n is the number of vertices in the network) that encodes the connected edges in a network. The number of neighboring vertices to each vertex in the network constitutes the degree of that vertex. The degree distribution of a network, which is essentially a histogram of the vertex degrees, provides a rough visual estimate of the connectedness within a network. When each non-zero entry to the adjacency matrix is weighted by the physical length of the corresponding edge, a weighted adjacency matrix is obtained that can be used to identify shortest paths between a desired origin–destination pair in the network.

1.1. Characteristics of regional railway and highway networks

The Shelby County, TN Railroad network (Int1) is adapted from the national railroad network obtained from the GIS data published by Federal Railroad Association (FRA). The Shelby County Highway Network (Int2) is adapted from the national highway network available in the FAF4 network database (Federal Highway Administration 2018). The level of granularity of this network includes interstates, state highways and local roads that provide access to various drayage/storage terminals and intermodal facilities. An overlay of the two regional networks is shown in Figure 1.

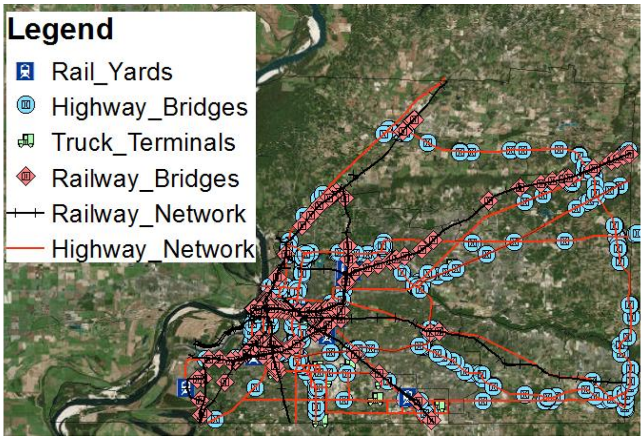

Figure 1: Regional Railway Network (Int1) and Highway Network (Int2) of Shelby County, TN

The railway network consists of 222 vertices and 267 edges. Each link is modeled as undirected, hence the resulting adjacency matrix is symmetric in nature. On the other hand, the highway network has 648 vertices and 691 edges. 87 bridges were identified in the railway network with details on structure type. Similarly, there are 325 highway bridges in the region as per the National Bridge Inventory (FHWA 2017) database. These bridges are mapped to their nearest network edge, so that at any instant, bridge closure is manifested as failure of the corresponding network edge.

1.2. Characteristics of Int3

The nationwide railroad network is a simplified adaptation of the FRA railroad network, using key vertex connectivity and edge length details. Vertices of the network are selected so that all the major CFS areas as per the Commodity Flow Survey (Bureau of Transportation Statistics 2012) database are covered, in addition to other major railroad hubs, as shown in Figure 2.

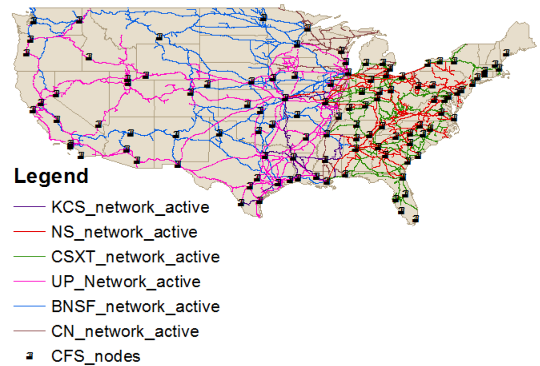

Figure 2: Simplified nationwide railroad network with each railroad represented by a separate color

Typically, individual railroads strictly operate on their own tracks unless appropriate trackage rights have been granted by the owning railroad. This is replicated by modeling the networks separately for individual railroads and combining them in a block diagonal matrix. Subsequently, links corresponding to the same city but different railroads are joined in the block diagonal matrix. In order to ensure that the network shortest path does not preferably jump between railroads unless necessary, a sufficiently large weight is assigned to these locations. This modeling approach provides for a future opportunity to consider sharing of trackage rights and consideration of the associated costs in resilience planning for railroad infrastructure.

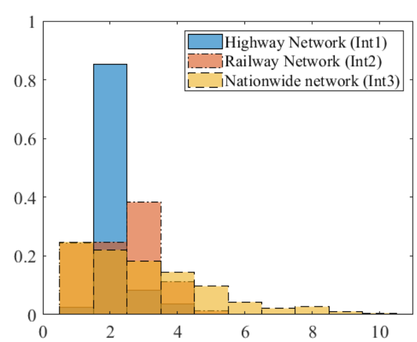

Figure 3: Degree distributions of all networks

A comparison of the degree distributions plotted in Figure 3 reveals that, while Int1 shows a fairly uniform distribution between degrees 1 and 3 with a mean degree of 2.4, Int2 has a sharp peak corresponding to degree 2 with a mean degree of 2.1. The degree distribution of Int3 reveals that the majority of the vertices have degrees between 2 and 5, with a mean of 3.1 and a maximum of 10 at the CSXT hub at Atlanta, GA. The vertex degrees shown here are railroad specific and do not account for locations where multiple railroads connect. Table 1 lists the top six railroad hubs in the US based on the cumulative vertex degree, as per the topology of the Int3 network model. Memphis, TN ranks sixth in order of cumulative vertex degree among US cities, with major railroads such as BNSF, UP, CN and CSXT operating within its boundaries, and five intermodal yards facilitating containerized freight transport.

2. OVERALL FRAMEWORK FOR NETWORK LEVEL RESILIENCE ANALYSIS

This study uses a probabilistic framework for assessing the temporal evolution of seismic resilience of the rail-truck intermodal network. Using Monte Carlo simulation, several spatially distributed damage scenario realizations are created for various instants of time after the hazard, spanning the duration of network recovery.

2.1. Details of framework

The first step in the framework involves simulating a scenario hazard, generating spatially distributed realizations of intensity measures (e.g. Peak Ground Acceleration) across the region of interest. In order to capture the effects of seismic damage on nationwide freight movement accurately, the damage scenario realization should include infrastructure components outside the region experiencing strong ground shaking. Following this step, physical damage scenario realizations are generated, using fragility curves for the vulnerable infrastructure components. Although railway and highway bridges are assumed to be the only vulnerable links in the network for the purpose of this study, it is acknowledged that railway tracks and roadways can also fail under earthquakes, a factor that can be easily incorporated into the framework in the future. In the next step, closure actions and estimated closure durations are assigned to each bridge depending on the damage level, for each scenario realization. At various time steps over the restoration timeline, the network state is evaluated and a resilience index is computed for the existing network state. The uncertainties propagated through the Monte Carlo simulations include uncertainties in damage state assignment, bridge closure decisions, duration of closure and in precise origin-destination (O-D) assignment. The O-D assignment is discussed in more detail in Section 2.3.

2.2. Input models and datasets used

The framework for resilience analysis of intermodal networks described in the previous section requires various input models and datasets at each step. The scenario seismic hazard is created using the mean of the predicted intensity measures from three ground motion attenuation models (Frankel et al. 1996, Somerville et al. 2001 Campbell 2003) for a specific point source (35.3° N, 90.3° W). Next, a spatially distributed scenario of bridge damage states is simulated across both the highway and railway networks, using highway and railway bridge fragility models respectively. For the purpose of this paper, highway bridge fragility models proposed by Nielson and DesRoches (2007) and railway bridge fragilities proposed by Misra and Padgett (2017a) are used. In order to capture the temporal evolution of network functionality, logic-tree based restoration models based on expert opinion surveys are used, for both railway bridges (Misra and Padgett 2017b) as well as for highway bridges (Misra et al. 2018). These models provide estimates of the probability of bridge closure and an estimated duration of closure for various bridge component level damage scenarios. Intermodal freight movement is modeled using the Commodity Flow Survey database (Bureau of Transportation Statistics 2012) is used.

2.3. Assumptions

The assumptions used for the resilience framework are as follows:

1. Bridges are the only vulnerable components of the network. Roads and railway tracks are assumed to be invulnerable in the results shown herein, although the framework allows roadway and railway track fragilities to be incorporated easily.
2. All bridge restoration work is assumed to begin simultaneously, immediately after the hazard. Future work can account for resource constraints and prioritization of restoration activities.
3. For each intermodal shipment, the local transfer from the source/terminal to the intermodal terminal takes place via trucks, while the long-haul transport takes place via rail. This assumption, although not accounting for flexibility in mode choices at all scales, is reflective of typical practice, as long-haul freight transfer is considerably more economical by rail.
4. Since exact O-D terminal locations are not listed in the Commodity Flow Survey database, the terminal is assigned by drawing at random from a list of likely candidate terminals for each freight shipment based on the type of freight and a prior knowledge of the type of freight handled at the stations.

3. SEISMIC RESILIENCE OF INTERMODAL NETWORK

The seismic resilience of the intermodal freight network is estimated by considering the combined performance of the three networks described in Section 1. The metric for seismic resilience used herein is abstracted from the definition provided by Miller-Hooks et al. (2012), where resilience is defined as the "fraction of demand that can be satisfied post-disaster".

3.1. Resilience definition

Leveraging the definition of resilience proposed by Miller-Hooks et al. (2012) and adapting it to a time-evolving framework, the following equation is used to quantify seismic resilience $\alpha(t)$ of the network at any given time t.

$$\alpha(t) = \frac{1}{\sum_{w \in W} D_w} E\left[\sum_{w \in W} d_w(t)\right] \tag{1}$$

where $d_w(t)$ is the post-earthquake performance index of the network for a specific O-D pair $w \in W$, D_w is the same performance index for O-D pair $w \in W$ calculated pre-event, W denotes the set of all O-D pairs of interest and the notation $E[X]$ denotes expected value of X. In order to capture the uncertainties stemming from distribution of damage, bridge closure decisions, closure durations and O-D assignments for individual shipments within Shelby County, the mean resilience index is calculated using $nsim$ distinct realizations for the same scenario earthquake.

The network performance index $d_w(t)$ is calculated as

$$d_w(t) = V_w \frac{1}{R_w(t)} \tag{2}$$

where $R_w(t)$ is a measure of minimum resistance along the path connecting the O-D pair w for the network at time t after the hazard, and V_w is the value of freight that needs to be transported between the O-D pair. At each time step, the path of minimum resistance is computed using a suitable graph theory algorithm, such as Dijkstra's shortest path algorithm. The reciprocal of pathway resistance function is used in this formulation, so that if the network is forced to choose a path of higher resistance, the performance indicator is reduced. Also, if an O-D pair is fully disconnected, the pathway resistance function $R_w(t)$ becomes infinity, implying that its reciprocal does not participate in the summation across all O-D pairs. The pathway resistance function can be used to represent the costs associated with freight shipment, including fuel costs, terminal delay costs and costs associated with procurement of trackage rights from a different railroad. The choice of optimal path at each time step thus depends on the chosen resistance function, and may not necessarily be the path of shortest distance or shortest travel time. For the purpose of this case study, the set $w \in W$ is assumed to denote all the possible O-D paths connecting the flows entering and leaving Memphis.

3.2. Resilience based on value weighted connectivity

In this section, the pathway resistance function is adapted to reflect O-D connectivity between all freight routes, as follows.

$$R_w(t) = 1 \text{ , if path } w \text{ exists} \\ \rightarrow \infty \text{ , if path } w \text{ does not exist} \quad (3)$$

For a single scenario, the network performance index $\sum_{w \in W} d_w(t)$ yields the expected dollar value of network throughput at any time t. When averaged over multiple scenarios, this index can be interpreted as the expected network throughput at time t after the hazard. Let the number of simulations carried out be n_{sim}, among which a path connecting O-D pair w exists in n_{up} cases. The value of $d_w(t)$ averaged over n_{sim} simulations is

$$d_w(t) = \frac{\sum_{n_{sim}} V_w \frac{1}{R_w(t)}}{n_{sim}} = V_w \frac{n_{up}}{n_{sim}} \quad (4)$$

When n_{sim} is sufficiently large, $\frac{n_{up}}{n_{sim}}$ can be interpreted as the probability that a path connecting O-D pair w exists at time t. Let this probability be represented as $p_w(t)$. Given that the value of shipment to be transported along path w is V_w, the expected throughput along the path connecting the O-D pair w is

$$|E(V_w)|_t = V_w p_w(t) \quad (5)$$

Hence, this interpretation of the network performance index is essentially an estimate of the expected fraction of pre-event throughput that the network can satisfy at any instant of time after the hazard. The resilience index is computed over 10,000 simulations, which is sufficient for convergence of both the mean and the standard deviation of the estimate.

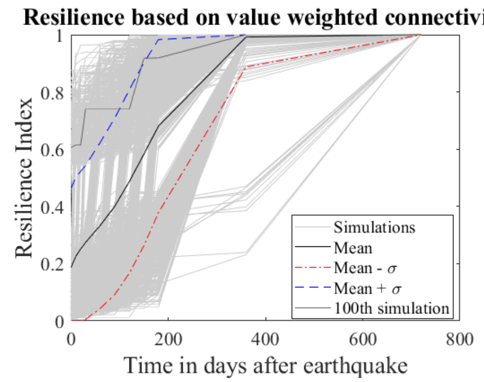

Figure 4: Evolution of value weighted connectivity based resilience index with mean and standard deviation across 10,000 simulations

The evolution of network resilience index is plotted in Figure 4 using the results from 10,000 network simulations. The uncertainty propagated across the simulations through the fragility models, the restoration models and the assignment of O-D terminals is represented in the form of the standard deviation bounds plotted in Figure 4.

3.3. Resilience based on value weighted inverse path length

In the second application, the distance along the shortest O-D path is used as the pathway resistance function as follows.

$$R_w(t) = L_w(t) \text{ , if path } w \text{ exists} \\ \rightarrow \infty \text{ , if path } w \text{ does not exist} \quad (6)$$

where $L_w(t)$ is the length of the path of minimum resistance connecting O-D pair w at time t. Thus, for a single scenario, the network performance index $d_w(t)$ thus is the sum of the reciprocals of shortest path lengths connecting each O-D pair weighted by the value of goods moving between the given O-D pair, as shown in Equation 7.

$$d_w(t) = V_w \frac{1}{L_w(t)} \quad (7)$$

This performance index may be interpreted as the cumulative value of goods per unit length moving between each O-D pair along the shortest path connecting them, per unit path length.

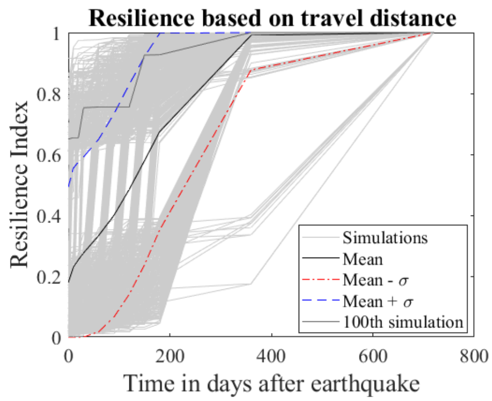

Figure 5: Evolution of travel distance based resilience index with mean and standard deviation across 10,000 simulations

The resilience index over 10,000 simulations, with the mean and standard deviation bounds, are shown in Figure 5. Although the plots in Figure 4 and Figure 5 show very similar trends, using path length as a penalty in the latter case allows each O-D pair to be in intermediate stages of restoration between disconnection and connection. These differences are more pronounced in the immediate aftermath of the hazard, when more links are damaged and the consequent effect on travel distances is more evident. This observation is illustrated by highlighting the 100th simulation in both Figures 4 and 5. Immediately after the hazard, the resilience index based on value weighted connectivity is 0.6 whereas the resilience index due to travel distance is 0.65; however this difference steadily reduces with time. When averaged over multiple simulations, the resilience indices in the two cases are almost equal. However, in the latter case, when travel distance is used in computing the resilience index, slightly wider standard deviation bounds are observed.

4. CONCLUSIONS

This study, as part of an ongoing work on quantifying natural hazard resilience of communities, provides a preliminary framework for resilience of rail-truck intermodal networks from a multi-scale perspective. The regional intermodal network is modeled with high granularity to account for local distribution of goods within the region, whereas the nationwide network is modeled with lower granularity to account for its effect on the distribution to and from all other destinations. Although the paper focuses on Shelby County, TN as a testbed network, the modeling framework may be adapted for similar applications at other locations for diverse natural or anthropogenic hazards.

The resilience framework used in this study builds upon previous studies on resilience of intermodal networks under disruptions to include a temporal component. In addition, a framework for a network performance index is defined using a pathway resistance function that can account for various costs associated with shipping freight. The resilience index is calculated for time evolving network states with gradual restoration of traffic on bridges. For the present study, two different adaptations of this proposed pathway resistance function are applied to the network. The first of these uses a binary function indicating whether a given O-D pair is connected, whereas the second one uses the actual distance traveled as a penalty function. However, the general formulation of this function can incorporate more detailed costs, with the optimal path being the one that minimizes the cost. Future work will, in addition to considering these additional costs, also consider optimal restoration scheduling based on relative bridge importance, improving on the current assumption that all bridge repairs begin simultaneously.

5. ACKNOWLEDGEMENTS

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