System-Based Resilience Assessment of Networked Transportation Systems in Metropolitan Areas: Case of Greater Los Angeles

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Abstract

One essential aspect of urban resilience is the ability of the transportation networks to maintain mobility and accessibility during the immediate aftermath, as well as in the long-term recovery, of an extreme event. Despite the critical nature of transportation services, the infrastructure inventory in many developed countries are in poor condition. For example, transportation infrastructure in the United States has repeatedly been graded poorly by American Society of Civil Engineers as it is aged and in need of a major retrofit or replacement effort. It is well established that topology-based approaches in transportation resilience abstract out network supply and travel demand relationships as well as fundamental traffic assignment concepts such as flow under capacity constraints. On the other hand, system-based approaches that are more promising in generating actionable policy insights lack the granularity enabled now by the recent advances in data and modeling, omit the scale of analysis required in metropolitan areas, and ignore formal considerations of the hazard itself which makes studies prone to simplistic what-if assumptions. To address such shortcomings, a preliminary framework intended to couple seismic hazard analysis with transportation network analysis is designed and deployed in a Greater Los Angeles Area case study where the impacts of a 7.3M scenario earthquake are investigated.

Introduction

Transportation networks are critical to the mobility of people and goods and are the backbone of the layered and interdependent network of civil infrastructures that facilitate everyday life. Due to their nature, they are exposed to a number of stressors including numerous natural and man-made hazards. In the case of natural hazards (e.g., earthquakes, hurricanes, etc.), the post-disaster functionality of transportation systems determine how rapidly the disaster-stricken area can recover (Chang, 2003). In the seismic regions of the US, transportation networks are especially vulnerable because of the current poor conditions of a significant portion of their bridges (ARTBA, 2018). As a result, resilience assessments of transportation systems have been a major research focus.

Research in this area is broadly categorized into two main categories of approaches: topology-based and system-based. Topology-based approaches are based on the graph-theoretic (nodes and edges) representation of transportation systems and quantify resilience in terms of network centrality based metrics such as betweenness centrality. Despite being practical in terms of data and modeling requirements, topology-based approaches often abstract out essential supply and demand relationships in the network (e.g., fundamental capacity-flow relationship). This makes them unable to generate actionable policy insights. For example, similar values of betweenness centrality in the abstract network may represent very different consequences in terms of how many travelers are affected and how large the total increase in travel time will be, depending on the demand and the availability and travel times of alternative routes in the real network (Mattsson and Jenelius, 2015). System-based methods founded on network supply and demand relationships are more promising in capturing the adverse impacts of hazard-induced disturbances on the transportation networks and their users. However, most system-based investigations of transportation resilience lack the granularity enabled now by the recent advances in data and modelling (road network and mobility data, software to simulate large scale models, etc.). There is also a tendency to test and validate approaches in small-scale networks omitting the scale of insights required by policymakers in metropolitan areas. Moreover, many studies analyze resilience via simple assumptions regarding the hazard without incorporating an understanding of the cause of failures (Khademi et al., 2015). The data and modelling needs in this area of research are discussed in detail in recent papers published by the authors (Koc et al., 2019; Cetiner et al., 2019) calling for holistic and coupled assessments of seismic hazards and the transportation disruptions caused by them. In this study, deploying a framework to address identified gaps, the authors investigate the transportation disruption resulting from a 7.3M earthquake affecting the Greater Los Angeles metropolitan area.

Background

By 2050, approximately 70% of human population will be living in cities (United Nations, 2018). Despite the well-known economic benefits of urban settlements, cities are known to be vulnerable to natural and man-made hazards due to their high concentration of people, capital and infrastructure. Many cities will face increasingly complex resilience challenges due to, for example, expected increases in the frequency and severity of extreme weather events, threats of terrorism, and risks due to active seismic faults near urban areas. The root of its definition originating from ecological resilience, urban resilience refers to *"the ability of an urban system - and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales- to maintain or rapidly return to desired functions after a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity"* (Meerow et al., 2016). In this definition, an urban system is characterized by its governance networks, networked material and energy flows, urban infrastructure and form, and socio-economic dynamics (Dicken, 2007). Among these constituents, civil infrastructure systems are the lifelines that supports the lives, interactions, and dynamics of urban dwellers; one of the defining attributes of urban dwellers is mobility. It is argued that transportation is the most significant lifeline, because disturbance to transportation imposes extra burden on the other lifelines (Hopkins et al., 1991).

Mobility is an immediate functional need in the aftermath of and during the recovery from disasters. Therefore, one essential aspect of urban resilience is the ability of the urban transportation networks to maintain mobility and accessibility during the immediate aftermath, as well as in the long-term recovery, of an extreme event. Despite the critical nature of transportation services, the infrastructure inventory in many developed countries is in poor condition. For example, transportation infrastructure in the United States has repeatedly been graded poorly by American Society of Civil Engineers as it is aged and in need of a major retrofit or replacement effort (ASCE, 2017). The presently poor condition of the transportation infrastructure is exacerbating the risk together with the backdrop of impending natural hazards. Large metropolitan areas that are already vulnerable to natural hazards (e.g., earthquake risk in the Greater Los Angeles Area, storm surge risk in Southeast US, etc.) are especially challenged due to the increasing exposure triggered by mentioned factors. These developments necessitate a quantified assessment of transportation resilience in metropolitan areas. This information is crucial for urban policy-making towards enhanced resilience in the long-run (Noulas et al., 2012, Brockmann et al., 2006), and for emergency response planning for a potential extreme event (Schneider et al., 2013, Aschenbruck et al., 2004, Song et al., 2014, Uddin et al., 2009, Lu et al., 2012).

Meanwhile, scalable urban mobility data and large scale travel models are increasingly available from both conventional and novel sources (Census Transportation Planning Products (CTPP), and mobility data from social media and smartphones, etc. (Jurdak et al., 2015, Song et al., 2010, Gonzalez et al., 2008)). Particularly, government initiatives for the development of large scale travel demand models by metropolitan planning organizations (MPOs), State Departments of Transportation, etc. create a unique opportunity for resilience research. Despite the availability of data and models, comprehensive investigations of resilience in the nexus of mobility are scarce.

Previous efforts have particularly fallen short in two major dimensions. First, there is a lack of utilization of explicit and holistic road network models of large metropolitan areas. This shortcoming results in an over-simplified physical abstraction of the transportation networks when they could explicitly be modeled (e.g., modeling freeways or major arterials only and neglecting surface streets), and does not allow realistic hazard simulations to be incorporated into the analyses. Second, the potential costs of mobility perturbation to communities have not been studied from a user-centric resilience perspective. In other words, mobility perturbations and impacts on travelers are not known at a high geographical resolution. These capability gaps impede the assessment of the burden urban dwellers have to bear as they recover from a disruption and prevents economic impact analyses and policy-making to focus on particularly vulnerable communities/segments within the larger urban ecosystem.

As such, there is a need for improved methodologies. To address the shortcomings of the literature in the area, these new methodologies need to be scalable in order to go beyond assessing the engineered resilience of an infrastructure component to assessing the resilience of transportation in metropolitan areas to enable actionable insights. New methodologies also need to incorporate formal considerations of the disruptive event (e.g., earthquake, flash flood, etc.) and identify direct damages based on infrastructure inventory data as well as state-of-the-art hazard analysis procedures. Moreover, they should incorporate the human stakeholders of the urban environment in order to quantify the mobility disturbance from a user-centric standpoint.

Methodology

The authors designed the preliminary framework on Figure 1 that couples seismic hazard analysis with transportation network analysis to achieve a high granularity, comprehensive resilience assessment while addressing the shortcomings discussed in the previous section.

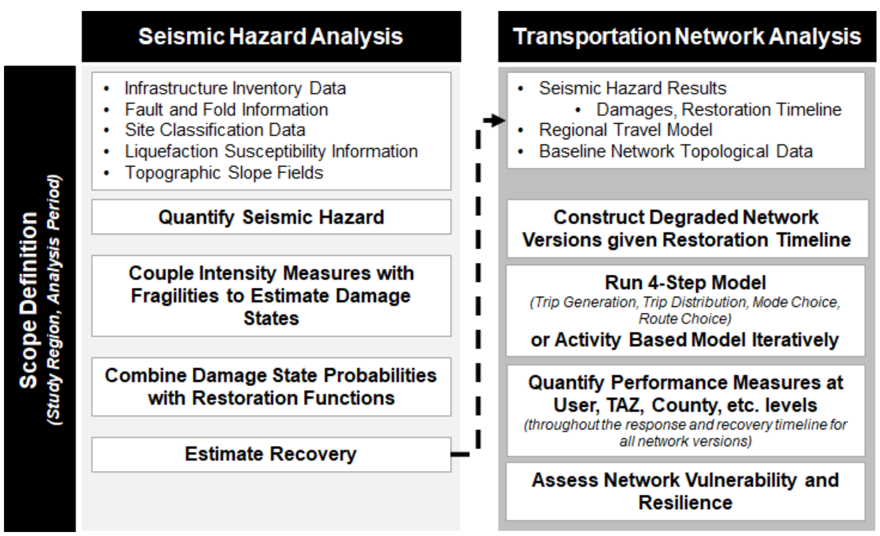

Figure 1: Preliminary framework for vulnerability and resilience assessments in metropolitan networks.

Seismic hazard analysis procedure of the framework begins with a scope definition (study region, analysis period) and a collection of datasets that provide infrastructure inventory data, fault and fold information, site classification, liquefaction susceptibility and topographic slope fields. Taking these datasets as inputs, seismic hazard analysis consists of three principal components: (i) quantifying deterministic seismic hazard governing an urban transportation network, (ii) coupling the intensity measures (IMs) resulting from the seismic hazard with component fragility functions to estimate the damage state probabilities, and (iii) combining the damage state probabilities with restoration functions to calculate the downtime of network components.

In simplest terms, deterministic scenario event for a region is identified as the event with the highest contribution to the IMs resulting from probabilistic seismic hazard (Cornell, 1968). For ground shaking due to earthquakes, this is typically performed by identifying the mode of the deaggregation plot for PSH (Bazzurro and Cornell, 1999) for 1-second spectral acceleration (S_{a1}) (Shafieezadeh et al., 2012). Once, the governing event is identified, then using the source information for the event and the site characteristics for all locations within the study region, S_{a1} at each site is computed using a ground motion prediction equation (Boore et al., 2014). These IM values are then coupled with fragility functions for the system components within the affected areas. For a set of IMs, the probability of a network component being in a damage state (P_j^k) is calculated as

$$\mathrm{P}_j^k = \begin{cases} \Pr(D^k \geq \mathrm{ds}_j) - \Pr(D^k \geq \mathrm{ds}_{j+1}) & j = 1,2,3,4, \\ \Pr(D^k \geq \mathrm{ds}_5) & j = 5. \end{cases} \tag{1}$$

For a set of IMs, expected downtime ($\mathrm{E}[D^k]$) is defined with respect to P_j^k using the recovery function for each damage state (RC_j) as in

$$\mathrm{E}[D^k] = \sum_{n=1}^{5} \mathrm{P}_j^k \cdot RC_j \tag{2}$$

where k is the index for IMs, $j$is the index for damage states, D^k is the damage state of network component due to IM_k, ds_1: no damage, ds_2: slight damage, ds_3: moderate damage, ds_4: extensive damage, and ds_5: complete damage states (Kiremidjian et al. 2006).

Physical damage and downtime findings are conveyed to transportation analysis and used to construct multiple network versions (pre-disaster baseline, post-disaster degraded versions). Given these network topologies (network supply), analysis includes (1) running a travel demand model iteratively; (2) quantifying network functionality indicators such as travel times, distances etc. at desired spatial resolutions and throughout the disaster timeline including response and recovery; (3) carrying out resilience assessment given functionality indicators.

Resilience of a system is analytically defined as

$$R = \frac{1}{h}\int_{h}^{h+t} Q(t)dt \qquad (3)$$

where t is the instant in which the disruption occurs and h is the investigated time horizon and Q(t) is an indicator of functionality. In other words, resilience is quantified as the area under the functionality curve with respect to 100% functionality throughout the investigated time horizon (See Figure 2). For transportation networks, several functionality indicators are proposed in the literature with system total travel time (Vehicle Hours Traveled: VHT) and total travel distance (Vehicle Miles Traveled: VMT) being common to most system-level indicators (Frangopol and Bocchini, 2011). Delay, as quantified by a volume-delay function (e.g., Bureau of Public Roads function), or average speed can also be used as network functionality indicators. The framework assesses resilience based on this definition of resilience for transportation systems.

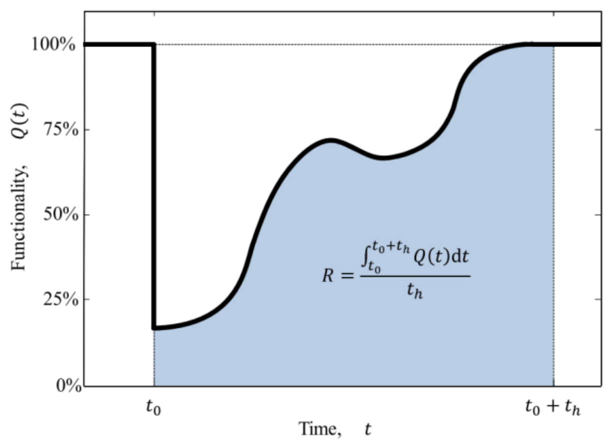

Figure 2. Network resilience curve adopted from Frangopol and Bocchini (2011).

Implementation of the transportation network analysis facet of the framework is based on a trip-based regional travel model developed by Southern California Association of Governments (SCAG). The trip-based model is developed periodically by SCAG--the metropolitan planning organization formed by the voluntary association of six Southern California counties including Los Angeles, Orange, Ventura, Riverside, San Bernardino and Imperial and it provides a common foundation for transportation planning and decision making by SCAG as well as other participating organizations (SCAG, 2016). The most recent version of the model is used by the authors with socioeconomic data from 2016. The model is highly granular and accommodates a holistic transportation network enabling a wide range of analyses including investigations of expansion projects, highway pricing strategies, introduction of new types of transportation services, etc. In accordance with the framework demonstrated above, the authors leveraged the model to determine the pre-disaster condition of the regional transportation network (baseline) as well as its condition in a post-disaster setting (day 30 after the earthquake).

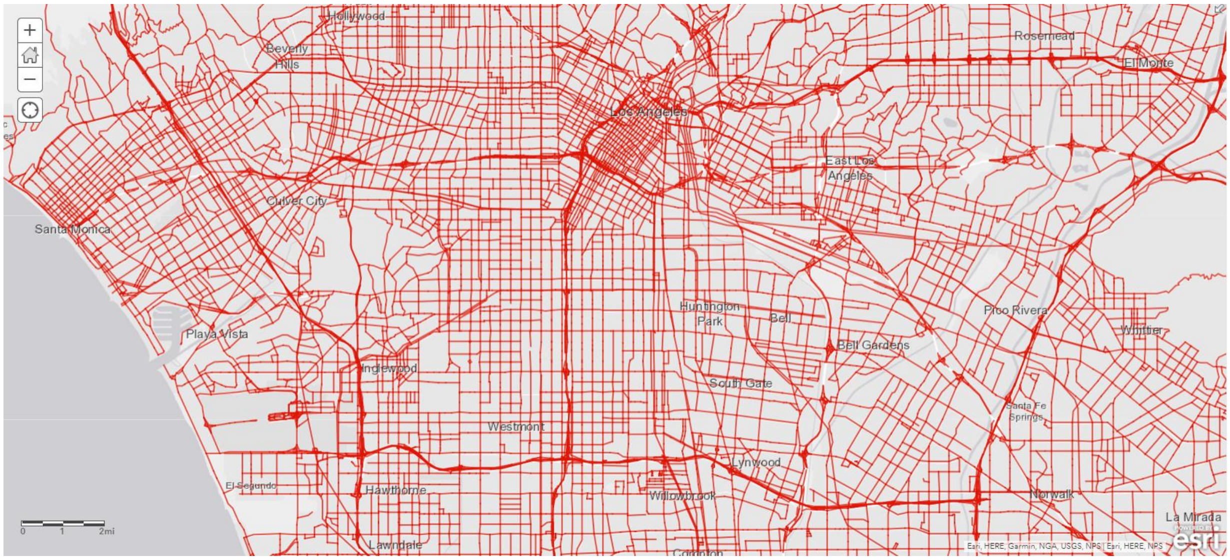

Figure 3. The level-of-detail of the underlying network model in SCAG RTDM. Red lines indicate network links.

Case Study

The authors deploy the framework mentioned above in a Greater Los Angeles Area case study. For this study, by disaggregating the PSH results for a return period of 975 years, the seismic event that has the greatest contribution to PSH results was identified as the M_w 7.3 earthquake caused by a rupture of the Palos Verdes Connected fault system at an epicentral distance 1.4 km off the Ports of Los Angeles and Long Beach. Using this event as the scenario earthquake, the ground shaking associated with the earthquake rupture was quantified by taking into consideration the relevant source, path (Boore et al., 2014) and site effects (Wald and Allen 2007). The damage to bridges in the study area was computed using the fragility functions developed for HAZUS (FEMA 2003). For computing the bridge functionalities 30 days after the scenario earthquake, recovery functions in HAZUS were used. A total of 55 bridges were determined to have a functionality level below 75% and deemed insufficient for operation.

The damage assessment results, i.e. closure of 55 bridges in study region on day 30 after the earthquake, are modeled in the SCAG RTDM (Regional Travel Demand Model) network by editing the network topology on TransCAD. The links that correspond to these bridges are deleted while ensuring connectivity of the remaining links around them. With the revised network, the trip-based model is run again to quantify the resulting mobility disturbance under fixed demand conditions. The comparison of baseline and post-disaster results reveals worsening network functionality indicators (delays, total distance/time traveled, etc.) due to the functionality loss induced by direct damages and paves the way for quantifying resilience. Table 1 presents the system-level travel time and distance functionality indicators (VMT and VHT) for baseline and day 30 model runs presented together with absolute differences and percent changes. It also presents disaggregated results for every county. Expectedly, VMT and VHT surge due to earthquake damage and Los Angeles County suffers the highest functionality loss. A striking result is that system TTT (total travel time) quantified as VHT increases by more than 20% throughout the SCAG region despite the relatively localized impact of the scenario earthquake with bridge closures mostly concentrated along three freeway routes (110, 710 and 405).

Utilizing the granular results generated by the SCAG RTDM, the authors also publish results online at the Tier 1 TAZ (Traffic Analysis Zone) level which is a zoning breakdown that divides the study region into more than 4,000 zones (https://arcg.is/1908zK). High granularity results and visualizations shared online enable local insights such as the identification of neighborhoods that experience more surface street traffic due to nearby highway link closures. Analytics in this context could go a step further to investigate emissions related externalities induced on neighborhoods, and open doors to environmental justice and transportation equity discussions. These research directions will be considered in authors' future work.

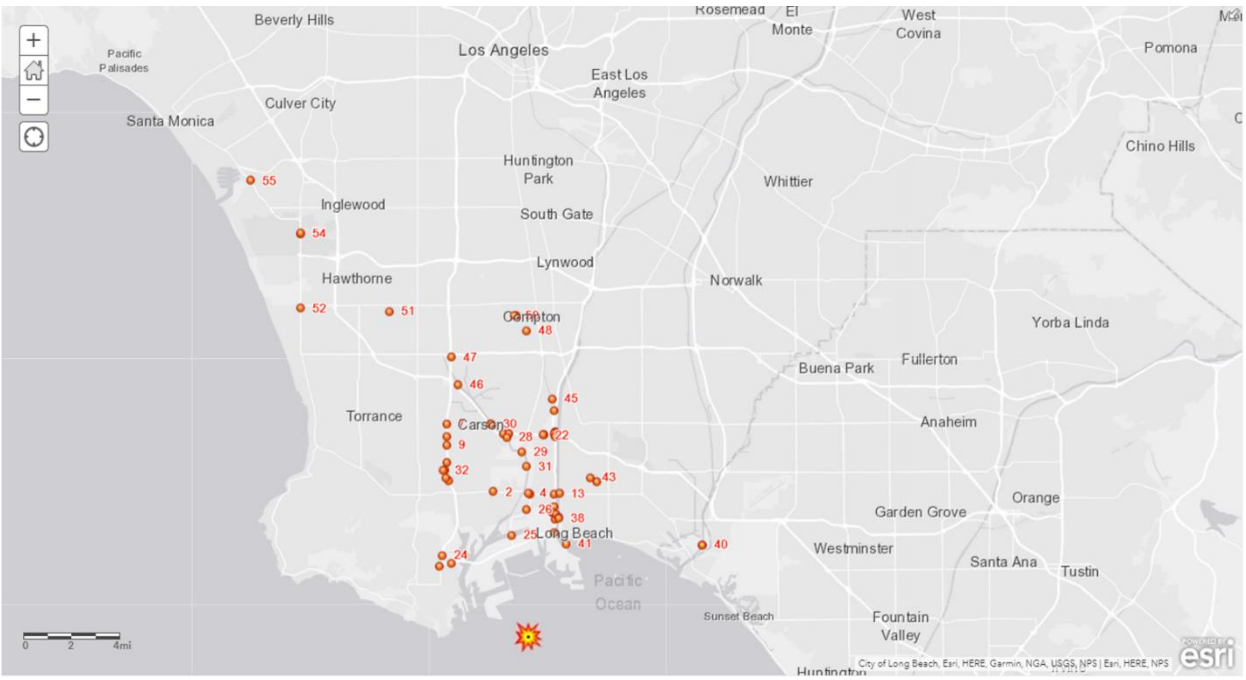

Figure 4. Bridges deemed closed on day 30 (red circles) after the scenario earthquake (epicenter marked with red/yellow star) according to the damage assessment.

Delays as quantified by the conventional BPR function are also quantified. Delay for the L&MDV class increase by as much as 71% where Los Angeles County experiences an 87.1% increase in delays.

Vehicle Miles Traveled (VMT) (miles)	Baseline	Day 30	Difference	% Change
VMT L&MDV	441,337,712	464,257,322	22,919,610	5.19%
VMT HDT	33,252,067	33,877,722	625,655	1.88%
VMT TOTAL (L&MDV+HDT)	**474,589,779**	**498,135,044**	**23,545,265**	**4.96%**
VMT by County (L&MDV+HDT) (miles)				
VMT Imperial	6,022,112	5,950,718	(71,394)	-1.19%
VMT Los Angeles	235,509,163	255,404,060	19,894,897	8.45%
VMT Orange	81,289,401	84,044,612	2,755,210	3.39%
VMT Riverside	64,087,908	64,101,547	13,639	0.02%
VMT San Bernardino	66,827,791	67,452,134	624,343	0.93%
VMT Ventura	20,853,404	21,181,974	328,570	1.58%

Vehicle Hours Traveled (VHT 1,000 hours)	Baseline	Day 30	Difference	% Change
VHT L&MDV	12,555	15,288	2,733	21.77%
VHT HDT	715	811	96	13.37%
VHT TOTAL (L&MDV+HDT)	**13,270**	**16,098**	**2,829**	**21.32%**
VHT by County (L&MDV+HDT) (1,000 hours)				
VHT Imperial	113,199	112,009	(1,189)	-1.05%
VHT Los Angeles	7,259,160	9,511,524	2,252,363	31.03%
VHT Orange	2,318,305	2,688,612	370,307	15.97%
VHT Riverside	1,465,415	1,533,608	68,193	4.65%
VHT San Bernardino	1,537,662	1,648,862	111,199	7.23%
VHT Ventura	538,659	566,336	27,677	5.14%

Table 1: System-level functionality indicators (VMT and VHT) for the pre-disaster baseline network and the degraded day 30 network. Results presented together with absolute differences and percent changes. L&MDV stand for light and medium weight vehicles (<8500 pounds in gross weight) and HDT stands for heavy-duty trucks.

Vehicle Hours Delayed (1,000 hours)	Baseline	Day 30	Difference	% Change
Delay L&MDV	2,651	4,551	1,900	71.66%
Delay HDT	144	215	72	50.05%
Delay TOTAL (L&MDV+HDT)	**2,795**	**4,766**	**1,972**	**70.55%**

Delay by County (L&MDV+HDT)	Baseline	Day 30	Difference	% Change
Delay Imperial	3	2	(0)	-2.17%
Delay Los Angeles	1,768	3,313	1,544	87.31%
Delay Orange	519	787	267	51.46%
Delay Riverside	188	247	59	31.30%
Delay San Bernardino	225	305	81	35.88%
Delay Ventura	92	112	21	22.60%

Table 2: Delays quantified per the conventional BPR function, presented for the study region as well as disaggregated to the county level.

Discussion and Conclusions

The framework designed by the authors to investigate transportation system resilience incorporates formal seismic hazard analysis procedures enriched by inventory data as well as a large-scale travel demand model. This coupled approach shows promise in addressing many shortcomings in the area mentioned in the earlier sections. The granularity of the analyses allows highly detailed visualizations related to the changing mobility pattern of the region.

One limitation of the case study is the conventional fixed demand assumption that ignores the potential travel behavior impacts of worsening network functionality. Travelers may chose to stay home, shift their demand to less congested times in the day, etc. Authors' investigation of resilience in metropolitan transportation systems has not focused on the post disaster travel behavior. However, SCAG's RTDM utilized in this study has sophisticated trip generation and trip distribution components that pave the way to study travel behavior. Moreover, this paper only presents network analysis results for two network versions, baseline and day 30 after scenario earthquake. The authors will publish results relating to the entire disaster timeline until full recovery in their future work. This way, a more comprehensive set of results demonstrating the pace of recovery will be obtained.

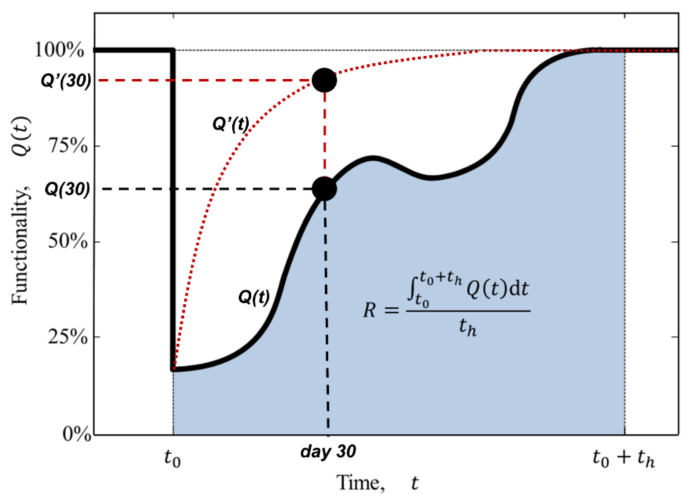

Figure 5. Network resilience curve adapted from Frangopol and Bocchini (2011) and revised. Dashed red line indicates faster recovery path achieved through implementation of resilience tactics.

Based on the resilience definition of Frangopol and Bocchini (2011), resilience is quantified—with respect to the continuous black line showing *Q(t)* on Figure 5—as the remaining functionality in the network following the disturbance stemming from direct physical damages to the infrastructure (e.g., bridge closures due to structural damages). This conceptualization of resilience is similar to the *static resilience* definition by Rose and Dormady (2018) which refers to *using remaining resources efficiently to maintain function*. In other words, static resilience in this context refers to the system-level indicators quantified by the user-equilibrium traffic assignment results under the new network supply conditions in the degraded network. Authors also intend to investigate *dynamic resilience* defined by Rose and Dormady which is characterized as *investing efficiently in repair and reconstruction in order to reestablish capacity as quickly as possible to regain function*. We indicate the improved recovery curve that may be achieved through *dynamic resilience* as *Q'(t)* on Figure 5. Some of the resilience tactics to achieve the faster recovery curve could be allocating resources to rapidly open critical corridors (e.g., I 405) to service or shifting heavy duty truck traffic to less congested time periods in the day to compensate for less desirable congestion levels due to the hazard.

The framework is currently being developed further to incorporate other hazards such as tsunamis and hurricanes. Moreover, the authors are focusing on advancements to the HAZUS inventories that have well-known limitations such as the use of archetype structures and a general lack of site-specific and structure-specific details. For this purpose, an image-based modeling approach is currently being integrated into the overarching framework to carry out more informed fragility analysis.

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