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TRAFFIC RESILIENCE MODELING AND PLANNING OF EMERGENCY MEDICAL RESPONSE

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16. Abstract

An efficient and timely rescue of injured people by emergency medical services (EMS) is essential to saving as many lives as possible following disasters. Disrupted traffic networks due to the failures of transportation infrastructure (e.g., bridges) following major hazards like earthquakes affect the accessibility and travel time of the disrupted transportation network during the emergency response stage. A rational prediction of the traffic network resilience performance in terms of EMS cannot only help implementing optimized post-disaster medical response plan, but also identify the most cost-effective preventive measures before the occurrence of disasters. Post-hazard EMS transportation highly depends on both medical needs of the vulnerable group and the serviceability of the disrupted traffic network.

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Traffic Resilience Modeling and Planning of Emergency Medical Response

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ABSTRACT[1]

An efficient and timely rescue of injured people by emergency medical services (EMS) is essential to saving as many lives as possible following disasters. Disrupted traffic networks due to the failures of transportation infrastructure (e.g., bridges) following major disasters like earthquakes affect the accessibility and travel time of the disrupted transportation network during the emergency response stage. A rational prediction of the traffic network resilience performance in terms of EMS will help implement an optimized post-disaster medical response plan, and also identify the most cost-effective preventive measures before disasters occur. Post-hazard EMS transportation highly depends on both the medical needs of the vulnerable group and the serviceability of the disrupted traffic network. A framework to assess the resilience performance of a typical traffic network in terms of post-earthquake EMS is developed by considering the complex interactions between building infrastructures, injured people, vulnerable medical centers, EMS vehicles, disrupted traffic networks, and natural hazards. Two resilience performance indicators are introduced to characterize the relative importance of different links in a traffic network and overall EMS resilience for the entire network. A virtual community is selected as the prototype to demonstrate the proposed framework, which is followed by a parametric study of the earthquake magnitude, different types of bridges, location and number of medical centers, and optimal location for a new medical center facility. The proposed framework and resilience performance indicators can help establish a more efficient pre-disaster improvement plan of critical links, prioritize post-disaster recovery, and optimize the strategic placement and resource allocation of an EMS medical center.

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1. INTRODUCTION

1.1 Background

Some natural disasters can cause extensive property damage, casualties, and injuries in very short time periods. Following an earthquake, for example, some of the most vulnerable buildings are destroyed or damaged and those residents who are severely injured may need immediate medical assistance and evacuation (Coburn et al. 1992). A functioning post-hazard transportation network is the backbone of supporting an effective emergency response, recovery efforts, and resilience of the entire community. Following a disaster, disrupted transportation networks, such as damaged bridges or roadways, may reduce accessibility and delay emergency response efforts. Such delays can be extremely critical to those who suffer severe injuries and are in dire need of immediate medical assistance. Thus, more rational post-hazard performance assessment and planning of EMS through a disrupted transportation network become vital.

Transportation network reliability defines the probability that a traffic system can meet a specified level of performance under a certain condition (Wakabayashi and Iida 1992). Most of the existing research efforts on traffic networks primarily focus on the reliability of intact networks during nonemergency circumstances by investigating travel time (e.g., Mahmassani et al. 2013; Guo and Williams 2015; Clark and Walting 2005; Wu and Zhang 2016), connectivity (e.g., Mahmassani et al. 2013; Guo and Williams 2015; D'este and Taylor 2003; Husdal 2004; Wakabayashi and Iida 1992; Jenelius et al. 2006; Kondo et al. 2012; Qian et al. 2012; Viriyasitavat et al. 2011), traffic capacity (e.g., Chen et al. 2002), accessibility (e.g., Nicholson 2003; Kondo et al. 2012), and trip cost (e.g., Bell 2000).

There are some existing studies related to emergency response and post-hazard traffic systems, in which the system's connectivity level was used as the primary performance indicator evaluated in a similar way as nonemergency connectivity studies (e.g., Scott et al. 2006; Viriyasitavat et al. 2011; Du and Nicholson 1997). Mete and Zabinsky (2010) developed a stochastic optimization model of medical supply location and distribution and EMS vehicle transportation plan in disastrous conditions. Dalal and Üster (2017) and Üster and Dalal (2017) presented an emergency network design model that integrated relief and evacuation considering the uncertainties of disaster location and intensity. Recently, Nogal et al. (2015, 2016, 2017) proposed some frameworks for the resilience assessment of transportation networks against extreme weather events and perturbations. Cost increment, user stress level, system impedance, and fragility curves of the traffic network were considered in the methodology. They also studied the uncertainties in the traffic demand, local vulnerability, and capacity of user response and developed the early warning system and decision support tools for the quick restoration of networks. Ganin et al. (2017) defined transportation network resilience as the change in the average annual delay per peak-period auto commuter resulting from roadway disruptions and compared the scenarios of different cities. Liao and Hu (2018) proposed a framework to assess transportation resilience based on traffic conditions and emergency management and derived the prioritization in the preparedness and recovery activities under budget constraints. Edrissi et al. (2015) proposed a disaster-based transportation network model based on connectivity and travel time and used death toll as the performance indicator. All these studies have their merits in studying emergency medical service or emergency relief supplies following hazards. However, there are some limitations of most existing studies (Novak and Sullivan 2014): (1) the complex interactions among transportation infrastructure vulnerabilities, people, EMS, and hazards have not been systematically modeled; (2) the limited resources during emergency response, such as personnel and vehicles, have not been realistically incorporated; and (3) most of the existing studies focused on recovery with limited information of critical links, which are substantial to the pre-hazard mitigation or reinforcement prioritization in the prevention stage (Edrissi et al. 2015; Holguín-Veras et al. 2014; Miller-Hooks et al. 2012).

This study aims to build a framework to assess the resilience performance of a typical traffic network in terms of post-earthquake EMS by comprehensively capturing the interactions between building infrastructures, injured people who may need EMS, disrupted traffic networks, limited EMS resources, and specific hazards. Two resilience performance indicators are introduced to evaluate the relative importance of different links in a traffic network and overall emergency medical response resilience for the entire network. With the two indicators, both post-hazard recovery strategies and pre-hazard prevention measures with the constraints of limited resources can be made. The proposed framework is demonstrated through a traffic network system with 20 zones, 33 links, and nine bridges in earthquake-prone areas, followed by detailed parametric analyses.

1.2 Organization of This Report

The report is composed of five chapters: Chapter 1 introduces pertinent background information and literature review results related to the present study. In Chapter 2, the model used in this study is introduced. In Chapter 3, the case study and parametric analysis are conducted. Chapter 4 gives a summary of this report.

2. MODEL DESCRIPTION

As shown in Figure 2.1, the proposed framework adopts the fragilities of bridges and buildings to obtain the failure rates of those structures following the hazard occurrence to derive information about the network connectivity ("supply") and the number and locations of vulnerable people who need medical assistance ("demand"), respectively. The states of a traffic network after a disaster and the corresponding probability of occurrence for each state are calculated based on the failure rates of bridges. Similarly, the number and distribution of injured people that need EMS are estimated based on the failure probability of buildings, as well as associated injury severities of each zone. In the proposed model, two resilience performance indicators specific to emergency response planning, evaluation, and improvements are introduced: total rescue time of the network and link importance values. These resilience matrices for emergency medical response can be applied in several stages of disaster response, such as prevention, emergency response, and recovery.

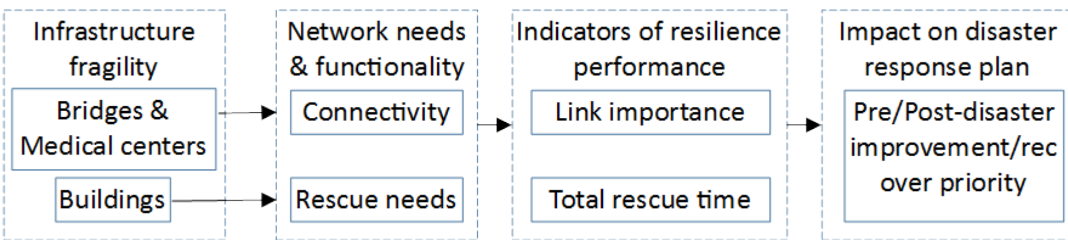


Figure 2.1 Flowchart of the modeling process

2.1 Seismic Fragility of Structures

The seismic fragility functions provide the conditional probability of exceeding a specified performance level given a set of seismic intensity measures, such as peak ground acceleration (PGA), spectral acceleration (SA), and spectral displacement (SD). The failure in terms of a limit state is defined as an excess of the limiting value of the performance indicator, such as stress and displacement of structures. There are many sources of uncertainties affecting the accuracy of the structural capacity. As a result, the seismic fragility of structures is usually presented as fragility curve(s) with an assigned probability to describe the confidence level associated with the estimation of fragility for each limit state.

For bridges, there are typically several different limit (damage) states, for example, no damage or slight/ minor damage, moderate damage, extensive damage, and complete damage (e.g., Choi et al. 2004). For each damage state, its probability is the difference between fragility curves corresponding to different limit state functions. In a region with different types of bridges (e.g., multi-span continuous slab/concrete/steel bridges, and reinforced concrete columns), the fragilities are also different for different bridge types (e.g., Choi et al. 2004; Gardoni et al. 2002 & 2003; Neilson and DesRoches 2007). From the perspective of emergency response of traffic networks involving bridges, a linkage must be built between the emergency management decision of a bridge (e.g., closure, partial closure, or open) and the physical damage state.

In addition to bridges, researchers have conducted extensive studies on the seismic fragility of typical buildings in a similar way (e.g., Reinhorn et al. 2001; Jaiswal et al. 2011). The seismic fragility of typical buildings can be used to estimate the injury severities of people residing in these buildings. The failures of the residential, commercial, and industrial buildings are further related to the injured population with existing knowledge about the occupancy, trapped people, and injured people. The details will be introduced in the next section.

2.2 Estimation of Vulnerable People Who May Need EMS

According to some existing studies (e.g., Coburn et al. 1992), the injured population of a building zone is related to the building collapse rate, occupancy rate, trapped rate, and injury rate. The failure rate of buildings under a given earthquake can be obtained through their seismic fragility performance as introduced in the previous section. The injured group of people can be quantified based on the population, average occupancy, building failure rate, trapped rate, and injury rate (Coburn et al. 1992):

$$\mathrm{b_z} = \sum_{u} \mathrm{Pop_z} * \mathrm{P_u} * \mathrm{M_1^z} * \mathrm{M_2^u} * \mathrm{M_3^u} \tag{1}$$

where $\mathrm{b_z}$ is the number of injured people of a given zone z; $\mathrm{Pop_z}$ is the population of a given community or zone z; $\mathrm{P_u}$ is the collapse probability of buildings type u. $\mathrm{M_1^z}$ is the average building occupancy of zone z, and $\mathrm{M_2^u}$ is the trapped rate of occupants in the collapse of building type u. $\mathrm{M_3^u}$ is the injury rate among the trapped population of building type u. $\mathrm{M_1^z}$ is related to the condition of the zone and time of the day. For instance, for residential zones, the occupancy rates are relatively low at daytime but high at nighttime, while they are opposite for the non-residential zones in urban places. $\mathrm{M_2^u}$ and $\mathrm{M_3^u}$ are related to the building type and the earthquake intensity. Usually, the higher the earthquake's intensity, the higher trapped and injury rates are of the same type of buildings.

2.3 Resilience Index and Link Importance Values

After an earthquake has occurred, the rescue time is an important factor to evaluate the effectiveness and success of emergency response efforts. The longer time it takes to rescue all the injured people, the higher the potential death toll may be. Therefore, network's total rescue time is used as the performance indicator of the traffic system in terms of emergency medical response, which needs to be minimized. The total rescue time is defined here as the total actual travel time on the roads during the round trip between the medical center and the site to pick up injuries. It does not include the delay time during the EMS process (e.g., temporary on-site medical care and transporting patients out of the buildings), which is assumed to be the same for all EMS trips in this study. After an earthquake, there are typically several damage states for a traffic system, such as various damage ranges of bridges or roadways. In this framework, only the bridge and medical center failures are considered as damage states of the traffic system, and each bridge will be in either "no failure" or "failure" states. Also, the medical centers are vulnerable under earthquakes, and each medical center will be in either "full functionality" or "closed for maintenance." If there are n_1 bridges and n_2 medical centers in the system, there will thus be totally $2^{(\mathrm{n1+n2})}$ possible states of the traffic system after an earthquake.

The emergency response performance can be assessed with optimizations on the total rescue time made for every possible state after an earthquake.

$$\text{Objective:} \quad \mathrm{T_s} = \min_{\boldsymbol{x}}\{\max_{\mathrm{p}}[\mathrm{T_s^p}(\boldsymbol{x})]\} \tag{2}$$

$$\text{Constraints:} \quad \mathrm{T_s^p}(\boldsymbol{x}) = \sum_{\mathrm{z}} \left(\frac{\boldsymbol{x}_{\mathrm{s}}^{\mathrm{p,z}}}{\mathrm{N_p}} \cdot \mathrm{t_s^{p,z}} \right) \tag{3}$$

$$\sum_{\mathrm{z}} \boldsymbol{x}_{\mathrm{s}}^{\mathrm{p,z}} \leq \mathrm{w_p} \quad \forall \mathrm{p,z} \in \boldsymbol{N} \tag{4}$$

$$\sum_{\mathrm{p}} \boldsymbol{x}_{\mathrm{s}}^{\mathrm{p,z}} = \mathrm{b_z} \quad \forall \mathrm{p,z} \in \boldsymbol{N} \tag{5}$$

$$\boldsymbol{x}_{\mathrm{s}}^{\mathrm{p,z}} \geq 0 \text{ and } \boldsymbol{x}_{\mathrm{s}}^{\mathrm{p,z}} \in \boldsymbol{Z} \tag{6}$$

where T_s is the optimal rescue time of the system under a certain state $s \in K$ (K is the set of possible network states after an earthquake); $\max_p\left[T_s^p(\boldsymbol{x})\right]$ is the longest rescue time among all the EMS centers and is defined as the rescue time of the system under network state s; T_s^p is the rescue time of EMS medical center in zone p under network state s; $t_s^{p,z}$ is the round trip travel time from zone p to zone z under a certain network state s. $x_s^{p,z}$ is the number of injured people being picked up from zone z and transported to the EMS medical center in zone p, and w_p is the capacity of the EMS medical center located in zone p. N_p is the number of EMS vehicles for EMS medical center in zone p, and $\boldsymbol{Z}$ is the set of integer numbers. The objective of this optimization is to minimize the total rescue time of the entire system. Equation (2) ensures that (1) the injured people are distributed to different medical centers in a balanced way so that every medical center can finish the rescue effort around a similar time, and (2) the overall rescue process is as quick as possible to save most lives.

Based on the optimization results from Equations (2) to (6), the resilience index of the traffic system is defined as:

$$\mathrm{RI}(\varepsilon) = \sum_{s=1}^{|K|} P\left\{\frac{T_0}{T_s} \geq \varepsilon\right\} \tag{7}$$

where T_0 is the optimal rescue time of the system when all the links are intact and all of the medical centers remain in full serviceability. ε is the level of functionality (LOF) criterion of the traffic system after an earthquake, which is a ratio between 0 and 1 to assess whether the reduced emergency response performance due to possible infrastructure disruptions is acceptable or not. ε is usually specified by the stakeholders as a subjective criterion.

In addition to the overall emergency response performance indicator, link importance value is very useful in terms of identifying the critical links from the perspective of EMS. Such information can be used to prioritize the reinforcement of the links before a hazard occurs or for emergency repair of damaged bridges immediately following the hazard to maximize the emergency response efficiency. The link importance of any link may be defined as the impact on the resilience index if that particular link fails. The more the resilience index drops once a link fails, the more critical that the link is to the EMS. To derive the link importance factor I_{ij}, the sample space of T_s is divided into subset ① where link (i, j) works and subset ② where link (i, j) fails (Edrissi et al. 2015). RI_{+ij} and RI_{-ij} are the resilience indices of subsets ① and ② respectively. Considering that $RI_{+ij} \geq RI_{-ij}$ and the link importance is negatively related to $\frac{RI_{-ij}}{RI_{+ij}}$, the link importance value of link (i, j) is defined as:

$$I_{ij} = 1 - \frac{RI_{-ij}}{RI_{+ij}} \tag{8}$$

which ensures that the link importance value $0 \leq I_{ij} \leq 1$.

3. CASE AND PARAMETRIC STUDY OF CENTERVILLE

3.1 Case Study of Centerville

Figure 3.1 shows the basic traffic network of a virtual community called Centerville, which has been used as a virtual test bed for several studies (Ellingwood et al. 2016). To demonstrate the proposed network under seismic hazards, this community is assumed to be in seismic-intensive regions. Some basic information of this network is shown in Table 3.1 and Table 3.2, and the length of each link is calculated from the longitudes and latitudes of the two nodes. For post-earthquake emergency response, the posted speed limits usually become irrelevant for privileged emergency vehicles. We conservatively assume the driving speeds of EMS vehicles are 30 mph for all roads considering there might be some debris, obstacles, or partial damage on the roads following the earthquake that may lower the actual driving speeds of EMS vehicles. It is apparent more accurate driving speeds that are specific to road conditions, if available, can be easily applied to the proposed framework in the future. The travel time for each link is obtained based on the link length and the driving speed of EMS vehicles. Each of the 20 nodes forms a zone in the whole community. It is assumed there are two medical centers offering EMS in the network, located in zone R3 and zone R5 (marked with stars in Figure 3.1), and are in relatively central locations of the community with close proximity to most of the nodes in the network. The two medical centers are special buildings and are considered as mid-rise concrete shear walls according to Hazus (1997). It is assumed in this study that a medical center will be closed for at least 30 days if it experiences extensive or complete damages. Or it will remain in full functionality. Zones I1 − I7 are mainly residential areas and the remaining zones are mainly non-residential areas; zones P1 − P6 are mainly commercial areas; and zones R1 − R7 are mainly industrial areas. In this study, only bridge damage may cause the links to become totally disconnected. The full closure caused by roadway damage due to earthquake is deemed rare and not considered in this study. Some possible minor or local damages on the roadways are reflected on relatively lower driving speeds of EMS vehicles throughout the network as introduced above. Nine out of 33 roads/links are therefore vulnerable to earthquakes due to the existence of bridges on these links (marked with the bridge symbols in Figure 3.1). There are three types of bridges in the community: multi-span continuous (MSC) slab, concrete, and steel. Because emergency medical response often occurs before transportation authorities can conduct comprehensive inspections of damaged bridges, it is conservatively assumed in this study that a bridge will be closed to traffic if it experiences extensive or complete damages as defined by the limit states. This is based on the understanding that a bridge may not remain opened either due to its apparent impassable nature caused by severe physical damages or decisions made out of caution by drivers based on their observations of extensive damage on the bridges.

The parameters in Table 3.2 are determined based on the zonal information. There are two different types of building materials in the community: masonry and concrete. For residential buildings, masonry structures are more popular while concrete structures are more popular for non-residential buildings like commercial and industry buildings. We randomly generated the percentage of masonry buildings between 50% and 100% for the residential zones and between 0% and 50% for the non-residential zones. Since this demonstrative example focuses on the movements of EMS vehicles instead of the medical service capacity of medical centers, it is assumed that the total number of people the two medical centers can accommodate is always higher than the total number of injured people being transported by EMS vehicles. In other words, each medical center will accommodate every patient being transported by EMS vehicles. According to U.S. ambulance statistics, there were 48,384 ambulances in 2008 when the U.S. population was 304.1 million (EMS Statistics 2017; Population in the U.S. 2017). To consider realistic emergency response resources, the total number of available EMS vehicles (Table 3.2) in the community is assumed based on its population with the same national ratio as illustrated above. The EMS vehicles assigned to the two EMS medical centers are roughly proportional to their capacities (total number of patients they can accommodate) so that all medical centers have the same "pick-up capability" (number of EMS vehicles/capacity).

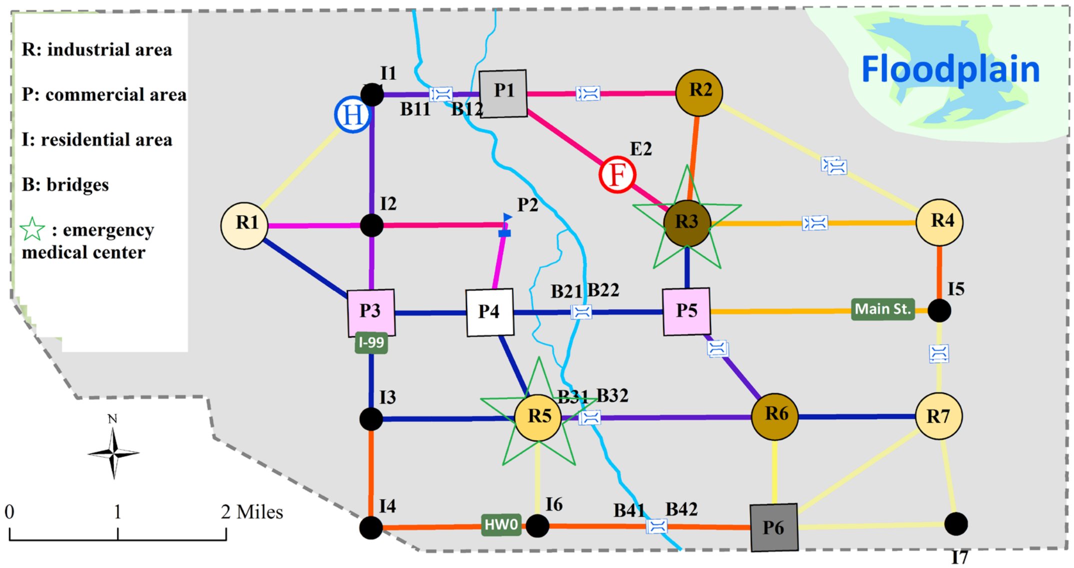


Figure 3.1 Traffic network of Centerville

Table 3.1 Link characteristics

Link#	Start zone	End zone	Length (km)	Travel time(min)	Bridges
1	I1	I2	1.9445	2.4306	0
2	I1	P1	1.594	1.9925	1 MSC-Slab
3	I1	R1	2.4817	3.1022	0
4	I2	P2	1.6246	2.0308	0
5	I2	P3	1.3118	1.6397	0
6	I2	R1	1.548	1.935	0
7	I3	I4	1.6205	2.0256	0
8	I3	P3	1.5741	1.9677	0
9	I3	R5	2.0231	2.5288	0
10	I4	I6	2.0231	2.5288	0
11	I5	P5	3.0653	3.8316	0
12	I5	R4	1.3118	1.6397	0
13	I5	R7	1.5741	1.9677	1 MSC-Concrete

14	I6	P6	2.8818	3.6023	1 MSC-Steel
15	I6	R5	1.605	2.0063	0
16	I7	P6	2.2073	2.7591	0
17	I7	R7	1.62	2.025	0
18	P1	R2	2.3757	2.9696	1 MSC- Slab
19	P1	R3	2.969	3.7113	0
20	P2	P4	1.324	1.6551	0
21	P3	P4	1.4407	1.8009	0
22	P3	R1	2.0321	2.5401	0
23	P4	P5	2.3909	2.9887	1 MSC- Concrete
24	P4	R5	1.6801	2.1001	0
25	P5	R3	1.3118	1.6397	0
26	P5	R6	1.9077	2.3847	1 MSC- Steel
27	P6	R6	1.6513	2.0641	0
28	P6	R7	2.5838	3.2297	0
29	R2	R3	1.9489	2.4362	0
30	R2	R4	3.5194	4.3993	1 MSC- Slab
31	R3	R4	3.0653	3.8317	1 MSC- Concrete
32	R5	R6	2.8813	3.6017	1 MSC- Steel
33	R6	R7	1.9924	2.4905	0

Table 3.2 Zone characteristics

Zone	Pop_z (person)	Masonry building (%)	Concrete building (%)	EMS capacity	No. of EMS vehicles
I1	8423	59.442	40.558	-----	-----
I2	10256	45.819	54.181	-----	-----
I3	9389	52.313	47.687	-----	-----
I4	6960	61.32	38.68	-----	-----
I5	9454	59.307	40.693	-----	-----
I6	14310	62	38	-----	-----
I7	15140	56.91	43.09	-----	-----
P1	4174	0.01	99.99	-----	-----
P2	7666	37.5	62.5	-----	-----
P3	5545	40.102	59.898	-----	-----
P4	5007	31.714	68.286	-----	-----
P5	3695	34.497	65.503	-----	-----
P6	7347	33.996	66.004	-----	-----
R1	7549	19.859	80.141	-----	-----
R2	8499	30.859	69.141	-----	-----
R3	7875	8.2284	91.772	182	6
R4	10129	32.697	67.303	-----	-----
R5	6768	0.012	99.988	304	10
R6	7727	14.117	85.883	-----	-----
R7	3674	0.3455	99.654	-----	-----

Assuming the depth of the epicenter in this study is 10 kilometers, we employed the seismic attenuation law developed by Atkinson and Boore (1995) for the mean PGA (cm/s^2):

$$\log(\mathrm{PGA}) = c_1 + c_2(M_L - 6) + c_3(M_L - 6)^2 - \log R - c_4 R \quad (9)$$

where M_L is the Richter magnitude; R is the epicentral distance (km); and c_1, c_2, c_3, and c_4 are parameters from regression analysis. According to the study by Atkinson and Boore (1995), the following parameters are selected: $c_1 = 3.79$, $c_2 = 0.298$, $c_3 = -0.0536$, $c_4 = 0.00135$.

To study the bridge failure risks during the occurrence of earthquakes, the fragility curves of similar bridges in a high seismic zone are adopted from an existing study (Neilson and DesRoches 2007). In the work by Neilson and DesRoches (2007), a bridge's fragility is defined as the probability that the seismic-induced demand meets or exceeds the seismic capacity of the bridge. The relationship between PGA and the extensive damage rates of the three types of bridges are shown in Figure 3.2. Since the extensive damage limit state in Figure 3.2 includes extensive and higher damage limits, the extensive damage rate can be used as the seismic failure rate of bridges for both extensive and complete damage limit states.

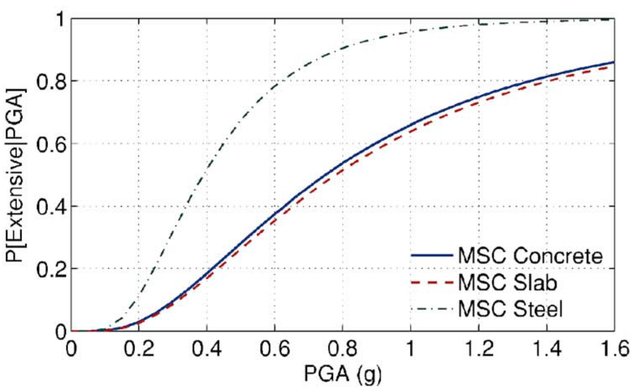


Figure 3.2 Seismic fragility curves for typical bridge types (Neilson and DesRoches 2007)

In the work by Neilson and DesRoches (2007), the probability of each damage state is:

$$P[Damage\ State\ i\ or\ greater|PGA] = \Phi[\frac{\ln(PGA) - \ln(med_i)}{\zeta_i}] \tag{10}$$

where med_i is the median PGA value of damage state i; ζ_i is the dispersion of damage state i. The median and dispersion values for seismic fragility curves of the three bridge types are presented in Table 3.3. According to Hazus (1997), Equation (10) also works for special buildings like medical centers with median and dispersion values of 1.24g and 0.64, respectively.

Table 3.3 Median and dispersion values for seismic fragility of five bridge classes

Bridge Class	Median PGA values (g) Extensive med_i	Dispersion ζ_i
MSC slab	0.78	0.7
MSC concrete	0.75	0.7
MSC steel	0.39	0.55

In this study, the failure of buildings is defined as the collapse since the number of injured persons caused by building collapse is the primary concern for EMS. Jaiswal et al. (2011) provided the relationship between Modified Mercalli Intensity (MMI) and the collapse fragility of several different types of buildings, which is

$$\mathrm{P_u(I_{mm}) = A_u \times 10^{(B_u/(I_{mm}-C_u))}} \tag{11}$$

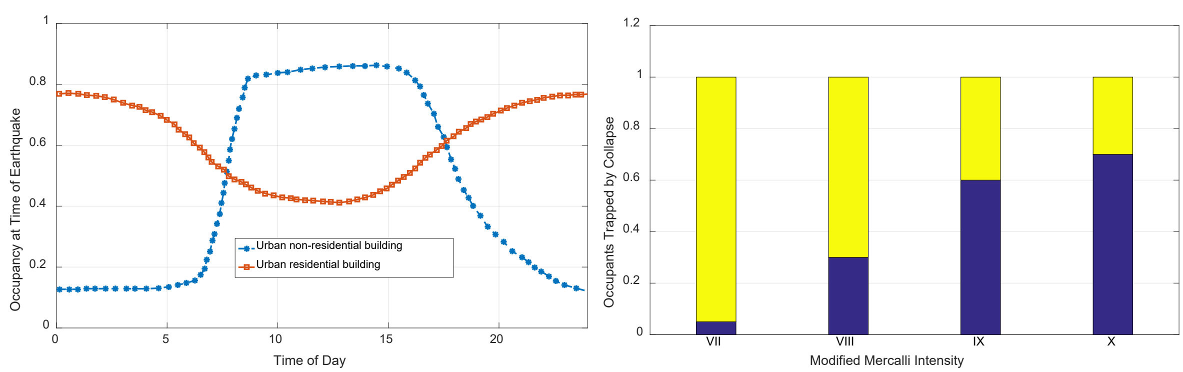
where $\mathrm{A_u}$, $\mathrm{B_u}$, and $\mathrm{C_u}$ are the scale, shape, and location parameters for building type u. The values of parameters A, B, and C are 0.85, -2.35, and 5.9 for precast concrete frame and 9.52, -4.89, and 5.32 for masonry buildings, respectively. $\mathrm{I_{mm}}$ is the seismic intensity related to the MMI scale. Wald et al. (1999) proposed the relation between PGA (g) and $\mathrm{I_{mm}}$ based on the analysis of earthquakes in California, which is

$$\mathrm{I_{mm} = 3.66\log(PGA) - 1.66 \quad for\ \ V \le I_{mm} \le VIII} \tag{12}$$

Based on Equations (11) and (12), the relationship between PGA and building collapse fragility can be derived:

$$\mathrm{P_u(PGA) = A_u \times 10^{(B_u/(3.66\log(PGA)-1.66-C_u))} \qquad for\ \ V \le I_{mm} \le VIII} \tag{13}$$

Coburn et al. (1992) studied the occupancy rate ($\mathrm{M_1^z}$) of urban residential and nonresidential buildings (Figure 4a) during a day and the occupants trapped rate by collapse for different macroseismic intensities with scale Medvedev–Sponheuer–Karnik (MSK). Musson et al. (2009) compared different macroseismic intensity scales, including MSK and MMI. Both MMI and MSK have 12 intensity levels from I to XII. According to Musson's study, any given ground motion has the same intensity level in terms of scales of MMI and MSK and thus they are practically interchangeable. In this demonstrative example, for the convenience of presentation, the occupants' trapped rates of masonry buildings based on MSK by Coburn et al. (1992) are converted to those based on MMI, as shown in Figure 3.3b. The trapped rate of concrete buildings under near-field earthquakes is 0.5. Figure 3.4 shows the distribution of different injury severities (i.e., light injury, hospitalization, severe injury, and dead) among people trapped by the collapse of masonry buildings and reinforced concrete buildings (Coburn et al. 1992).



a. Occupancy rate of urban buildings

b. Occupants trapped rate by collapse of masonry buildings

Figure 3.3 Occupancy and trapped rates by collapse (Coburn et al. 1992)

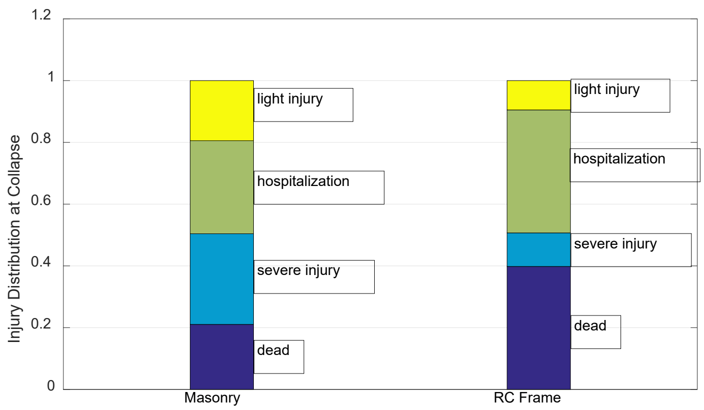


Figure 3.4 Injury distribution among trapped people (Coburn et al. 1992)

For EMS, the focus is apparently on those who were considerably injured but still remained alive after the earthquake. Among all the injured people, those with severe injury and hospitalization levels in Figure 3.4 may need immediate medical care and will receive EMS priority. The scenario earthquake is assumed to happen at 10:00 AM, and the average occupancy of residential and non-residential buildings can be obtained from Figure 3.3a. Similarly, the other parameters under two different earthquake magnitudes can be calculated with Equations (9-13), and the details are summarized in Table 3.4.

Table 3.4 Model parameters derived from Richter magnitudes

Richter magnitude	6.5	7.25
PGA (g)	0.2988	0.4486
I_{mm}	7.37	7.93
P_u of RC frame	0.0213	0.059
P_u of masonry	0.039	0.127
Failure rate of MSC-slab	0.08	0.19
Failure rate of MSC-concrete	0.09	0.21
Failure rate of MSC-steel	0.31	0.56
M_1^z of residential zones	0.42	0.42
M_1^z of nonresidential zones	0.85	0.85
M_2^u of masonry	0.143	0.282
M_2^u of concrete	0.5	0.5
M_3^u of masonry	0.6	0.6
M_3^u of concrete	0.5	0.5

As discussed earlier, there are nine vulnerable links in the traffic system with bridges involved and two vulnerable medical centers. Any of the nine links and the two medical centers is possible to fail during an earthquake, so the total number of possible states K for the traffic network after an earthquake equals 2^{11}. The depth of the epicenter and the epicentral distance are assumed to be 10 km and 26.5 km, respectively. Considering both are much bigger than the linear size of the community, it is assumed that the whole community shares the same PGA and other seismic characteristics. In this study, the graph theory and Dijsktra's shortest route algorithm (Dijsktra 1959) are applied to analyze the shortest routes between nodes for each possible state after a hazard. Let the LOF $\varepsilon = 0.85$ and $M_L = 6.5$, the link importance values and system indicators, are calculated with the framework introduced above and the results are listed in Table 3.5 and Figure 3.5. Genetic algorithm and sequential quadratic programming are used to optimize the total rescue time [Equation (2)] with integer constraints for variables on a desktop computer with a 3.2GHz processor and 16GB RAM, and the computational time is about seven minutes.

Figure 3.5 shows considerable difference among the importance values of different links from the EMS perspective. Links 32 and 14 are found to be the most important links while links 18 and 30 are the least ones in the network. As shown in Figure 3.1, it is apparent that links 18 and 30 are redundant and there are better alternative routes that can bring the EMS vehicle to the EMS medical center from the same area.

Table 3.5 System indicators when $M_L = 6.5$

	$M_L = 6.5$
Rescue time (min)	264.3
RI	0.9317
T_0 (min)	207.1

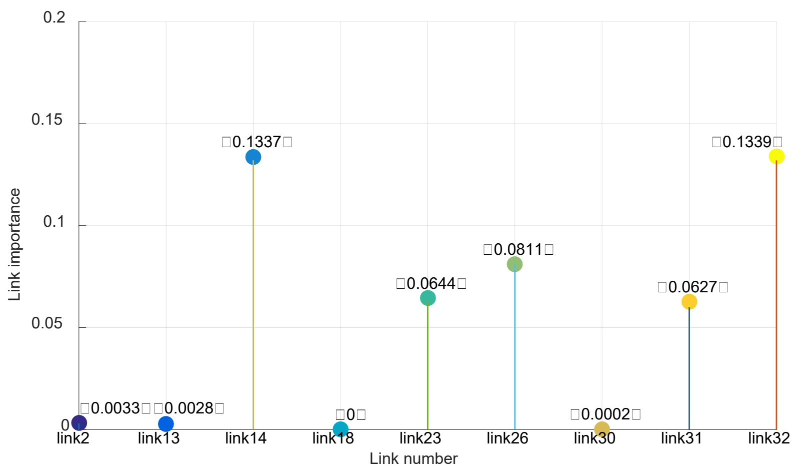


Figure 3.5 Link importance values when $M_L = 6.5$

3.2 Parametric Analysis

Parametric analyses are conducted with the proposed framework on different parameters, such as level of functionality, Richter magnitude, bridge types, number and location of EMS medical center, and possible new addition of an EMS medical center.

Level of functionality ε

As introduced previously, the stakeholders may specify the level of functionality as a type of subjective performance expectation, and such a value may have influence on the resilience index and link importance values. The influence of the LOF ε on network indicators is analyzed, and the results of several selected links are shown in Figures 3.6-9. Figures 3.6-8 show that link 2, 13, 14, 23, 26, 31, 32 are most sensitive to the value of LOF ε and links 18 and 30 are the least. It is consistent with what has been observed from Figure 3.1 that link 18 is always redundant in the system. There are several peaks in Figure 3.8. Taking link 18 as an example, when the LOF is larger than 0.7, the failure or functionality of link 18 has little impact on the acceptability of the network performance for all possible network damage states.

When the LOF ε is around 0.67, link 18 has moderate effect for some network damage states. In Figure 3.9, a relatively faster reduction in network reliability is observed when LOF increases. It is because most values of T_s concentrate within a narrow range around T_0. This phenomenon is caused by the relatively low failure probability of the medical centers and bridges, especially for the MSC slab and MSC concrete bridges under $M_L = 6.5$, and the complexity of the traffic network. When a network becomes more complex, a link is more likely to have alternative links with similar travel time in the network.

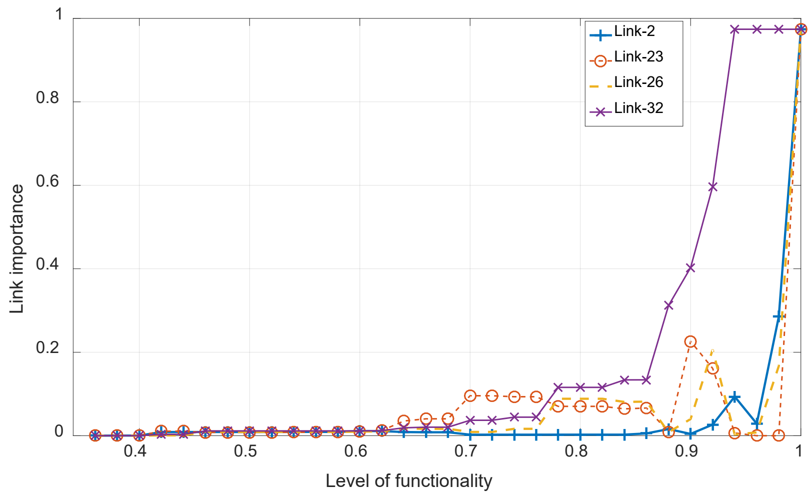


Figure 3.6 Link importance values (link 2, 23, 26, 32) as a function of the level of functionality

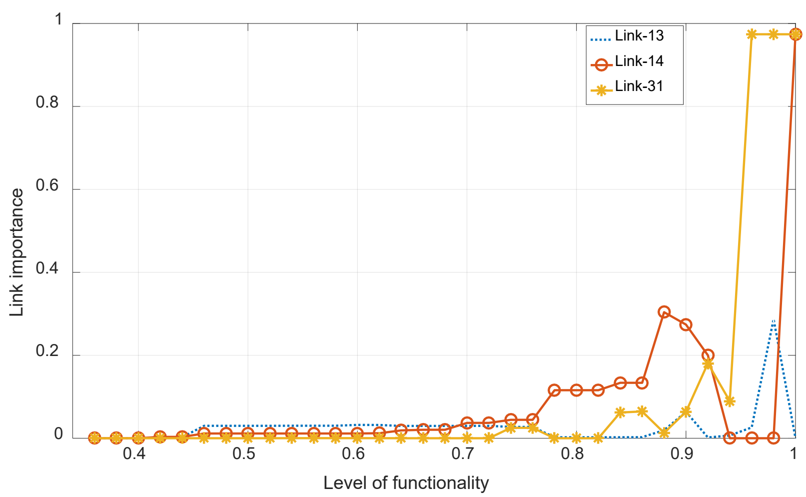


Figure 3.7 Link importance values (link 13, 14, 31) as a function of the level of functionality

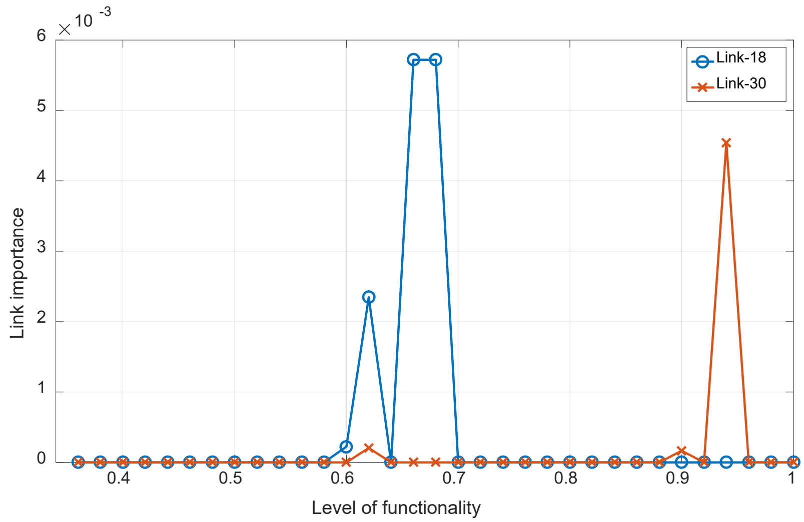


Figure 3.8 Link importance values (link 18, 30) as a function of the level of functionality

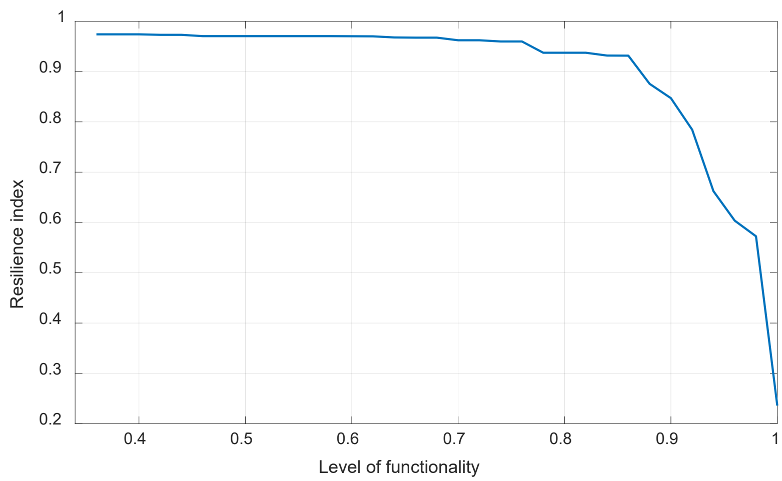


Figure 3.9 Resilience index as a function of the level of functionality

Richter magnitude

The influence of Richter magnitude on the system is based on its influence on the fragilities of residential buildings and bridges. In this study, another Richter magnitude is also applied to make a comparison, i.e., $M_L = 7.25$. When $M_L = 7.25$, the failure probabilities of buildings, MSC slab bridges, MSC concrete bridges, and MSC steel bridges get higher. As a result, the higher the Richter magnitude is, the more injured people and the more vulnerable links (i.e., bridges) of the traffic network there will be. In reality, the EMS capacity of a medical center may not be sufficient for a higher number of injured people who all need immediate medical attention during a very short time period under a high seismic magnitude like 7.25. In this case, additional overflow or a temporary medical center is assumed to be made available in zone I1 also with a mid-rise concrete shear wall. It is assumed the overflow or temporary medical center in zone I1 has the same "pick-up capability" as the original medical centers; the pick-up capability of a medical center is the ratio of its number of EMS vehicles to its capacity. The link importance values and the comparison of the rescue time and reliability are shown in Figure 3.10 and Table 3.6.

By comparing Figure 3.5 ($M_L = 6.5$) and Figure 3.10 ($M_L = 7.25$), it is found that the link importance values change considerably under different seismic intensities. Different from the case with $M_L = 6.5$ (Figure 3.5), when $M_L = 7.25$, link 2 becomes the most significant one and link 18 is no longer the least important one (Figure 3.10). Due to the change in the medical resources/supply condition caused by the overflow or temporary medical center at zone I1, link 2 becomes very critical and link 18 is no longer redundant. Table 6 lists the results of the total rescue time and resilience index under two magnitudes. It shows that magnitude has a significant effect on the system resilience and the rescue time in a complex way since different magnitudes of earthquakes affect both "supply" (connectivity and travel time due to possible bridge failure) and "demand" (injury caused by building damage) of the system. Therefore, post-earthquake EMS planning may have different optimal strategies when earthquakes with different intensities occur.

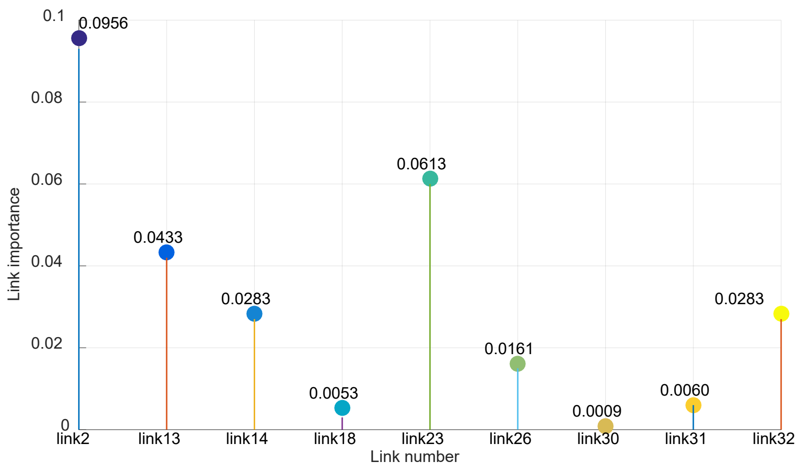


Figure 3.10 Link importance values when $M_L = 7.25$

Table 3.6 Comparison of system indicators at different magnitudes

	$M_L = 6.5$	$M_L = 7.25$
rescue time (min)	264.3	574.9
RI	0.9317	0.8451

Bridge types

Three types of bridges have been considered in this study with certain ratios of composition. Apparently, different kinds of typical bridges have different seismic responses and failure probability. Accordingly, the connectivity conditions of the system will also change. Three special cases are studied for comparison purposes: case 1–all bridges are MSC slab ones; case 2–all bridges are concrete girder ones; and case 3–all bridges are steel ones. The three cases are analyzed under seismic excitations with both $M_L = 6.5$ and $M_L = 7.25$. The total rescue time results are listed in Figure 3.11.

Figure 3.11 shows that at both Richter magnitude and the composition of different bridge types have considerable influences on the network efficiency and total rescue time. Compared with that, when $M_L = 6.5$, a larger difference exists among different bridge composition scenarios when $M_L = 7.25$. The results suggest that detailed classification of bridge types with considerably different seismic fragilities may be more critical for areas experiencing higher seismic intensities than lower intensities. Comparatively, the adoption of more MSC slab or girder bridges may potentially reduce the total rescue time or increase the system emergency response reliability. Steel bridges may cause the largest impact on increasing the total rescue time. More general conclusions, however, can only be made based on studies of more traffic networks with site-specific details. But this type of information, if available to a specific community, can be very helpful to the planning efforts of future pre-hazard bridge strengthening, post-hazard repair prioritization, and the design of new bridges when post-earthquake EMS performance is of concern.

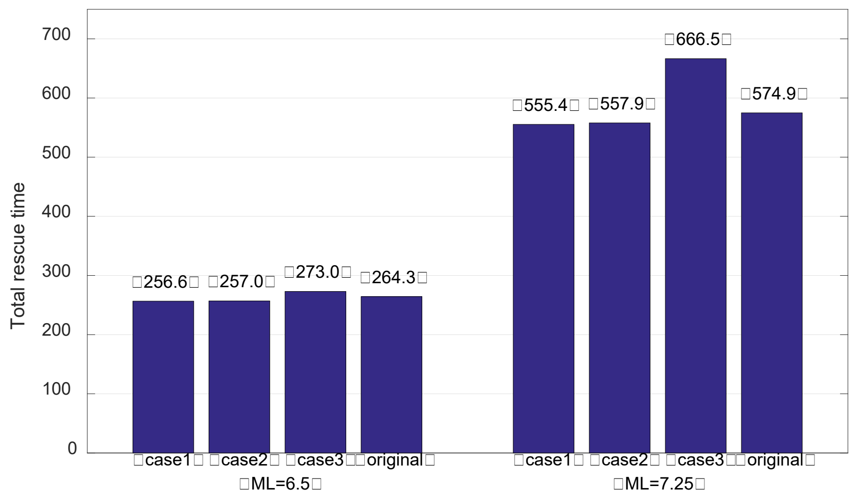


Figure 3.11 Total rescue time (min) in different cases/magnitudes

Location/number of EMS medical centers

The location and number of medical centers supporting EMS in a community are apparently important decisions, and strategic and optimized planning can achieve the best balance between saving more rescue time and economic efficiency. In the proposed framework, such parameters deserve further investigations since they can directly affect the supply of emergency medical response. To make more insightful observation of the impacts from these parameters, it is assumed there is only a centralized EMS medical center in the community in this section. With only one EMS medical center, a wide range of possible locations of the centralized EMS medical center in the network can be investigated to disclose the effect of an EMS medical center's location on emergency medical response performance as well as possible optimal locations. For parametric and comparative study purposes, the total demand of the EMS traffic (i.e., total patients needing to be transported), the community's total medical center capacity and the number of total EMS vehicles remain the same as the ones in the previous sections. Each of the 20 zones is studied as a possible candidate of the centralized EMS medical center, so the system indicators of 20 different potential medical center locations are compared. Figures 3.12-13 list the resulted link importance values and total rescue time.

Figure 3.12 suggests that the locations and number of EMS medical centers affect the importance values of individual links significantly. For some medical center locations (e.g., I1, I6, R4, R6), the link importance values of one or two links become very critical, justifying higher priority of enhancement or maintenance on those links before and restoration after an earthquake. For some medical center locations, such as I2 and I3, the link importance values of most links are similar, indicating even contributions to the emergency response of the whole network. As discussed earlier, link importance is only one side of the coin by showing the relative relations of different links. The other important performance indicator is about the total rescue time of the network, which directly defines the overall emergency response performance of the whole network.

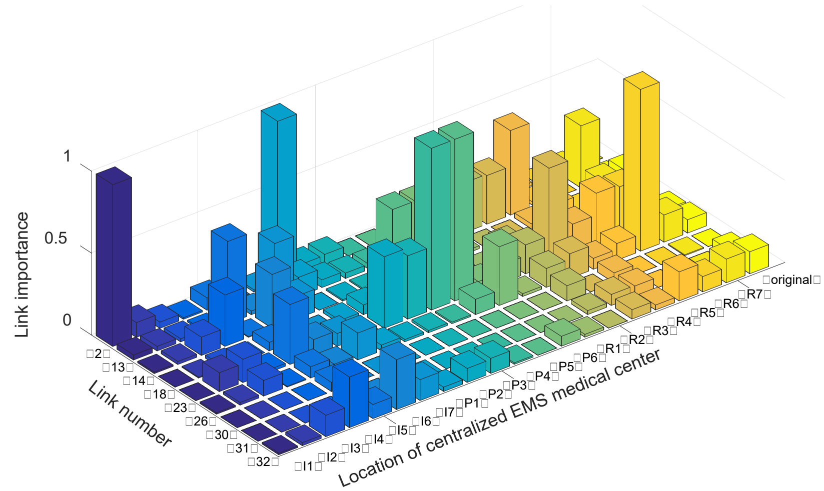


Figure 3.12 Comparison of link importance for different location/number of EMS medical center(s)

Figure 3.13 shows there is a big difference between the rescue time results when the location of centralized EMS medical center changes. When the centralized medical center is located at P4 or P5 zone, the community is most efficient in terms of total rescue time. It is due to the relatively central locations of the two zones and there are only one or two vulnerable links (with bridge) connected to them. Locating the centralized EMS medical center at I7 zone leads to the highest total rescue time since I7 is at a corner of the community and surrounded by four vulnerable links (with bridges reducing the accessibility of the system). When compared with the original case, all the comparison cases show higher total rescue times, and it is apparent that an additional EMS medical center in the original case can greatly increase their accessibility for the entire system. It is noted that the analysis in this section is for demonstration purposes of the proposed methodology. If site-specific data for a particular community are available, a detailed analysis can be made following the same procedure introduced above to provide important planning information of the EMS medical center.

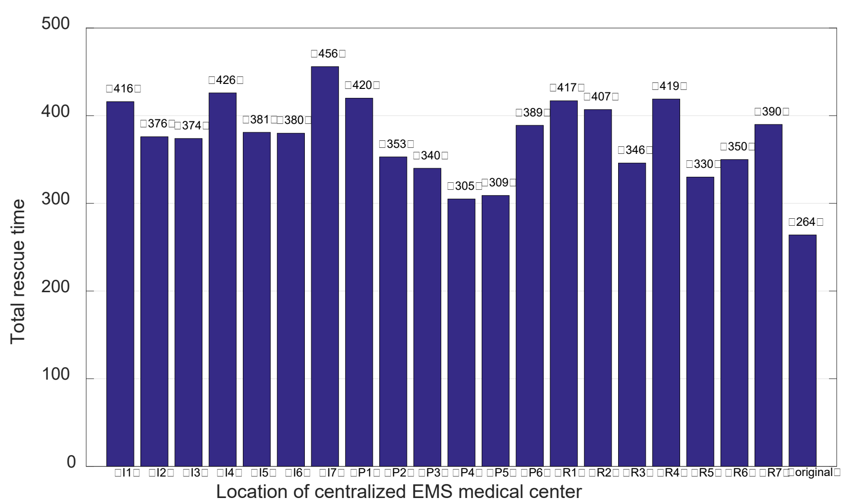


Figure 3.13 Comparison of total rescue time (min) for different location/number of EMS medical center(s)

Best location of a new additional EMS medical center

For a community with population growth over time or simply a need to improve the emergency response reliability of the community, sometimes it is warranted to build a new EMS medical center. In this study, if people build a third EMS medical center in one of the remaining zones, the entire network's accessibility may increase, and in turn, so does the resilience of the traffic system. In this section, investigations are made to identify the optimal locations of the new facility and possible impacts to the emergency response performance of the whole community. Suppose that each zone is a possible candidate for the third EMS medical center except zones R3 and R5 (which already have EMS medical centers) and it is assumed that the new EMS medical center can accommodate 90 people with three EMS vehicles. The resulting link importance values and total rescue time of each candidate are calculated and shown in Figures 3.14-15.

Figure 3.14 shows that the location of the new medical center has a great influence on the link importance. There are some locations with new EMS medical center, such as I7, P6, R6, and R7, that will cause overall reduced link importance of the whole network. This can be interesting information for traffic management and public health authorities to evaluate the current link conditions or decide between focusing the limited recovery/resources on the functionality of several critical links and spreading the resources to more links with less dependency on individual ones. Figure 3.15 shows there is big difference between the rescue times among different medical center candidates. When the new additional EMS medical center is located at zone I7, P6, R6, or R7, the traffic system is most efficient in terms of rescue time. The four zones located at a corner of the community and all the links connecting these zones to the rest of the community are more vulnerable. By considering both the results of link importance and total rescue time, building a new EMS medical center among the four zones (i.e., I7, P6, R6, or R7) has the most significant impact on the EMS performance of the whole community.

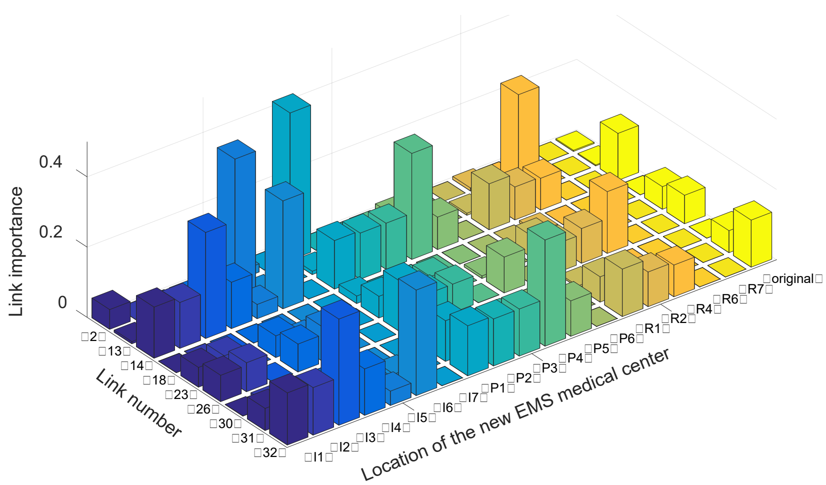


Figure 3.14 Comparison of link importance for different locations of the new EMS medical center

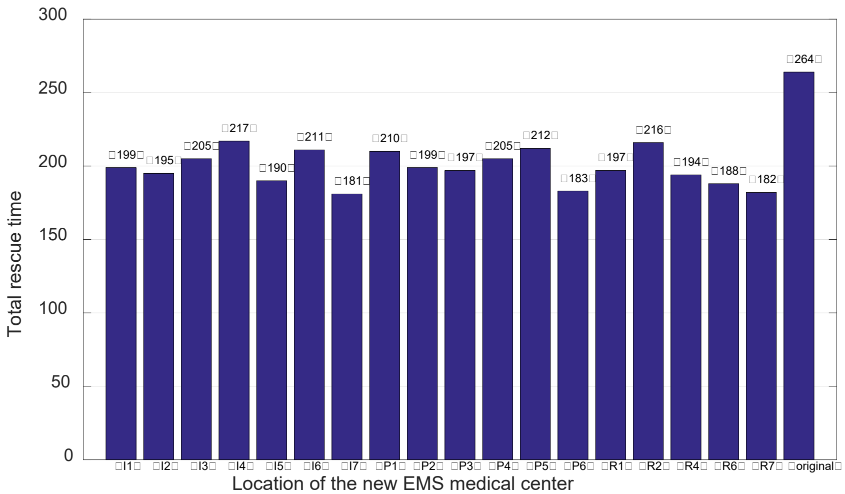


Figure 3.15 Comparison of total rescue time (min) for different locations of the new EMS medical center

4. CONCLUSIONS

Emergency response is a very critical stage following any major hazard or incident. A framework of modeling resilience-related performance of a transportation network following an earthquake was developed from an emergency medical service perspective. In the model, fragility information of both the buildings and bridges were adopted to quantify the number and locations of people who may need emergency medical assistance and possible disruptions of the links, respectively. Two resilience performance indicators were introduced to evaluate the relative importance of different links in a traffic network as well as the overall emergency medical response efficiency for the whole network. The importance information of links can be used to develop a more efficient pre-disaster improvement plan and post-hazard emergency recovery strategy by keeping those links with higher importance robust and passable in both preparation and emergency response stages. In the meantime, the overall emergency medical response resilience can assist with evaluating the emergency response performance of the whole community, conducting performance-based intervention and design optimization, and developing a more rational emergency response plan for a community. Finally, the proposed framework was demonstrated in a virtual community following a seismic event. A parametric study was conducted to study the impacts of several important parameters of the model under two scenario earthquake intensities. The possible addition of new EMS medical center was also studied to find out the optimal locations and possible outcome. The results show that the seismic magnitudes considerably affect the number of severely injured people needing emergency medical assistance and, at the same time, change the network connectivity. The proportion of different bridge types has a great influence on the connectivity and total rescue time of the network. The locations and number of the EMS medical centers affect the total rescue time notably since they impact the accessibility of the EMS. The best location for a new EMS medical center is sensitive to the site-specific vulnerability of infrastructure in the community and requires a case-by-case study to maximize the impact. Although this study was demonstrated through an earthquake hazard, the proposed framework can also be extended and applied to more diverse scenarios with different hazards or incidents.

This study has limitations: (1) only full closure of bridges was considered and no special case of limited passage such as by emergency vehicles on bridges was considered; (2) due to the scope limit, EMS facility capacity reduction following hazards was not considered in detail in this study. More realistic medical service capacity variations of each individual medical center due to, for example, power outage during earthquakes, can be considered in the future studies; (3) possible debris, obstacles, or damages on roads were reflected only on relatively lower driving speeds of all EMS vehicles, which were the same throughout the whole network. With road-specific speed characterization with possible debris, the EMS vehicle driving speeds may be adaptive to the specific disruption scenarios of the road in the future studies; and (4) the proposed framework was demonstrated with limited damage states of infrastructures in a moderately sized community. For a very large and complex community with higher number of limit states, more efficient optimization algorithms may be required to maintain reasonable computational efforts.

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