IDENTIFYING NETWORK-WIDE CRITICAL TRANSPORTATION LINKS UNDER DISASTER DISRUPTIONS: A MULTI-SCENARIO AND PROBABILITY-BASED SIMULATION APPROACH

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ABSTRACT
Critical infrastructure systems have received significant attention over the past several decades. Transportation system is among many critical lifelines that communities or any urban areas are dependent on. Disruption analysis of transportation infrastructure thus is important to ensure the prevention, preparedness, response and recovery from any risks. In the context of transportation network, identifying critical links under disaster disruption scenario can help guide pre-disaster preparation and post-disaster recovery efforts. Previous studies for disaster-based transportation network analysis were not carried out within a probabilistic context, owing to analysis methods that either look at single link impact or focus on specific disruption scenario. We advance existing knowledge by presenting a probabilistic approach to simulate various disruption scenarios and identify the most critical links within the network. Our method takes advantage of Monte Carlo simulation, network-wide demand modeling, and regression analysis to address the probabilistic nature of disaster effect and capture the joint impact of links failures. Applying to the Salt Lake County transportation network in the State of Utah, our analysis effectively categorizes the links based on their vulnerability and criticality for disaster prevention and preparedness. The proposed method can be easily transferable to different transportation networks regardless of scale, topology, and the type of the disasters that might impose disruption.

KEYWORDS: Network-disruption; Monte Carlo; Linear regression; Simulation; Critical infrastructure

INTRODUCTION

Critical infrastructure systems include all the basic organizational structures and physical facilities required for the day-to-day operation of society. Transportation infrastructure (e.g. roads, bridges, and rails), among many other critical infrastructures, is subject to disturbances from natural, technological and malicious sources *(1–5)*. Such disruptions to the system, caused by any source, are costly. For example, the recent collapse of the Interstate 10 "Tex-Wash" bridge in California, which was caused by a combination of structural deficiencies and severe flooding *(6)*, resulted in an \$8 million cost to replace the bridge and an estimated \$1.5 million of unexpected costs to travelers and businesses and 19,000 wasted hours for truck drivers, per day, when it was completed closed *(7)*.

In an effort to mitigate the infrastructure disruptions and economic losses, these systems should be designed with a mechanism for resiliency and robustness, providing the ability through which to resist potential risks, absorb the initial damage, and recover to a stable condition *(8)*. For transportation infrastructure, where resiliency is concerned, many steps have been taken to ensure the continuity of the system, from retrofitting bridges, to developing priority road maps *(9, 10)*. For most regions/communities, the road system is the most important transportation asset, supporting a wide variety of modes, including auto, bus and bicycle. Road networks also serve as the primary infrastructure for providing access to important lifelines in a community, including emergency services, as well as healthcare and education. During extreme events, transportation networks can hinder the ability of restoration equipment to reach areas requiring restoration *(11, 12)*. This often manifests as lengthy detours. Problems also arise for neighborhoods that rely upon a single connection (e.g. bridge) to the transportation network. When that connection is damaged, neighborhoods can become completely isolated from the remainder of the grid.

A myriad of studies have been conducted to model the transportation network disruption of various scales and identify the critical components within the network *(13–18)*. The main purpose of this scientific corpus is to develop techniques that can effectively model the impact of disasters through performance evaluations (i.e. travel time, accessibility) to minimize risk and vulnerabilities of the network. General approaches include empirical methods such as scenario-based, simulation, and optimization techniques. One common interests of these studies *(13–16, 18)* is to identify the individual impact of roadway links in terms of network performance (e.g. average travel time) upon disruption. This is usually achieved by removing one vulnerable link at a time and evaluate the network performance. The drawback for such analysis is the lack of consideration on the local hazard probability. That is, the influence of the likelihood of link damage and the probability of combined link failure is not thoroughly considered. As a result, a link with low probability of hazard exposure but geographically "important" might be considered as a critical link, while in fact, it may not be of high priority for pre-disaster preparation or post-disaster cleanup. Furthermore, overlooking the joint impact of multiple link failures might undermine the important role that certain links serve in terms of connectivity even though they might carry marginal traffic.

The contribution of this paper is thus twofold. First, this study captures the link damage probability by generating multiple real-world scenarios (instead of one) through a combined Monte Carlo simulation and network simulation. The generated scenarios ensure the impacts of link damage probability to be thoroughly considered and the network-wide transportation performance to be fully captured. Second, the analytical framework, developed on the basis of the simulation results and regression analysis, allows the vulnerable links to be identified to further guide pre-disaster retrofit efforts.

Previous studies on network disruption analysis will be discussed in the following section. We will argue that the empirical methods for disaster based transportation network analysis has not been thoroughly conducted within a probabilistic context, owing to analysis methods that either look at single link impact or focus on specific disruption scenario. Our proposed method is presented, which takes advantage of Monte Carlo simulation and regression modeling to address the probabilistic nature of disaster and capture the joint impact of links failures. The method is applied to the Salt Lake City transportation network to showcase its effectiveness. Implications and results are discussed at the end.

LITERATURE REVIEW

The first network disruption studies aimed to evaluate the negative impact of a disruption scenario on transportation network performance. Asakura used travel time reliability to evaluate the impact of deteriorated roads on capacity degradation. Travel time reliability is defined as a function of the ratio of travel time in degraded and non-degraded condition *(19).* Giuliano and Golob assessed the impact of Northridge earthquake on travel patterns in two damaged corridors. Their results revealed that the most important change in travel patterns in post-disaster condition is the flexibility of travelers in choosing available alternatives. Based on their analysis, most of travelers adjust to the new condition by changing routes, travel time schedules, and avoiding trips in the damaged areas *(3)*. Chang and Nojima utilized Network coverage and transport accessibility to evaluate the impact of earthquake on rail and highway transportation network performance in Kobe, Japan. They reported that both transportation networks experienced extensive damage in the disaster but service restoration proceeded more rapidly for rail network *(5).* Disruption scenarios used in these studies is based on the level of damage to different transportation network components. Various approaches were utilized to model the impact of disasters in term of different performance measures. Scenario-based assessment *(3, 5, 13, 14, 16, 18, 20)*, simulation-based assessment *(15, 21, 22)*, and optimization-based assessment *(17, 23, 24)* are among the most common approaches used for network disruption assessment.

Scenario-based approaches specify a particular scenario or small set of scenarios and evaluate their impact on network performance. The probability of scenario's occurrence is not considered in this approach. Simulation-based approaches generate a large number of scenarios for assessment. Scenarios are generated based on damage probability of vulnerable components. Optimization-based approaches seek to identify the worst case scenario which will result in most adverse impact on network performance *(12, 25)*.

A vast majority of network disruption studies concentrate on evaluation of network capability to deal with disaster consequences *(12)*. A few studies tried to develop strategies for managing network in disaster condition. A common concern among these studies is to identify critical components of transportation network and prioritize them for pre-disaster preparation and post-disaster recovery effort *(13-15, 26, 27)*. For pre-disaster condition the critical components ranking can help decision makers to prioritize component for retrofitting investments. In post-disaster condition, the components ranking can be used to allocate available resources to competing recovery projects.

A comprehensive review of network disruption literatures reveals that various measures were utilized to quantify the impact of network disruption on individuals, community, and economy *(12)*. Network robustness *(13, 14, 28)*, resiliency *(23, 24, 29)*, accessibility *(5, 18, 30)*, economic loss *(26, 31, 32)*, reliability *(15, 21, 22)*, total travel time *(20, 27)*, risk *(5, 33, 34)*, and vulnerability *(16, 17, 30)* are some of the performance measures used by past studies. Various definitions were introduced for some of these performance measures. Robustness measures the ability of network to withstand disturbances and maintain some level of functionality after disaster occurrence. Reliability is the probability that a system preserves its functionality after a disruption event. Resiliency can be defined as the ability of any network to resist and absorb the impact of disruptions. Risk is a term used to represent both likelihood and consequence of any disruption event. Vulnerability considers the potential consequences of a disruption event but does not account for disaster event probability *(12)*.

Majority of past studies assess consequences of network disruption and links importance by removing each link from the network one at a time and evaluating their respective effects on network performance *(13–16, 18)*. There are two major drawbacks to this approach. First, such method does not consider the disruption probability of each link, so the link importance is only dependent on the impact of link disruption on network performance measures. Second, removing an individual link from a network is an unrealistic simulation scenario since after a disaster, it's more likely that several links fail or suffer extensive damage together *(16)*. Other approaches employ optimization model to identify the worst case scenario and links with highest priority for improvement *(17)*. However, the link importance can change at different disruption levels. Therefore, it's not reasonable to determine links' importance based on a specific disruption scenario.

METHODOLOGY

To facilitate the network-wide disruption analysis, this study is decomposed into two major components. First, multiple real-world scenarios accommodating various damage levels are generated. The level of damage to the vulnerable links (a.k.a. bridges) in each scenario is determined by performing Monte Carlo simulation based on bridge fragility curves *(35)*. The bridges capacity reduction at each scenario is then determined. The probability resulted from Monte Carlo simulation in each scenario is fed into a computer simulation for network-wide traffic assignment modeling, and for assessing the network performance. Second, regression modeling is used to associate vulnerable links (a.k.a. bridges) capacity reduction to network travel time increase. Note that each scenario is treated as one observation sample. The estimated parameters reflects the impact of each vulnerable link (a.k.a. bridges) to the network.

It is important to mention that this study focuses on the types of disasters that are not life threatening yet would cause damage and prevent the normal operation of critical infrastructure system (i.e. transportation network). Under such assumption, we expect that people would resume their daily activity pattern within a short time period, and thus negligible changes would occur in travel demand. Therefore, we model "business-as-usual" traffic flows and examine how normal demand will be accommodated post disaster.

Disruption Scenarios Simulation

In reality, the exact level of damage that a disaster might produce to the transportation network remains unknown until it actually occurs. Depending on the nature of a disaster and the link resistance (ability to withstand a disaster and maintain its functionality), multiple extents of damage could happen post disasters. On the other hand, the importance of each individual link is a function of its own characteristics and the damage condition of other links. By modeling the varying combinations of damaged links in each scenario, it is expected that links' importance would change accordingly. In network disruption analysis, it might not be reasonable to determine the importance of a link via a single scenario (e.g. the worst case scenario). Instead, for disaster preparation or post disaster recovery purposes, the modeling effort should be conducted on the basis of all possible scenarios. To enable such analysis, first, Monte Carlo simulation is conducted to populate the possible scenarios by estimating the probabilistic damage extent of each link. Monte Carlo simulation is a sampling procedure used to propagate uncertainties in model inputs into uncertainties in model outputs *(36)*.

In this study, we focus on the potential link damage induced by earthquake in Salt Lake County, Utah. We estimated potential damage caused by lateral spread ground deformation to roadways and bridges. Lateral spread displacement map and lateral spread fragility curves were used to estimate potential damage. Fragility curves specify the damage states based on the estimates of lateral spread. For each bridge, lateral spread displacement is estimated based on collected boreholes at bridge location. Lateral spread displacement is then used to determine damage probability on fragility curves. Since there is uncertainty in lateral spread displacement, Monte Carlo simulation is utilized to propagate these uncertainties into potential outcomes (bridge damage states). Interested readers can refer to Moriarty *(37)* for further details on the estimation of lateral spread and associated damage. Five possible damage states were considered for each bridge including collapse, extensive, moderate, slight, and none damages. Various damage states cause different level of capacity and free flow speed reductions which negatively affect the transportation network performance. Capacity and free flow speed reductions associated with each damage state were estimated from the study conducted by Bartlett et al. *(38)* and illustrated in Table 1.

TABLE 1 Road Capacity and Free Flow Speeds due to Damages

Link Damage State	Capacity Change Rate	Free Flow Speed Change Rate
None	100%	100%
Slight	100%	75%
Moderate	75%	50%
Extensive	50%	50%
Collapse	0%	0%

The probability resulted from Monte Carlo simulation is fed into a computer simulation for network-wide traffic assignment. Network Explorer for Traffic Analysis (NeXTA), an open-source dynamic traffic assignment tool, is utilized in our study for traffic flow modeling. NeXTA can be used for large-scale transportation simulation. It enables planners and engineers to assess effect of various strategies or investments on traffic operation. Modeling impact of work zones, freeways, and tolling facilities are some of the important applications of this software. NeXTA outputs are set of links volume and network average travel time calculated for each disruption scenario. Figure 1 shows the pseudo code of disruption scenarios generation and traffic simulation. The code consists of two inner loops nested in scenario. In each scenario iteration, the first loop generates the real-world scenario of links capacity reduction. The second loop utilizes the results of the scenario generation to calculate the capacity reduction impacts on total network travel time. The output will be K scenarios, containing the damage states of each link and average network travel time at each scenario.

```
function disruption_scenario_simulation
    for k = 0; k < K; k = k + 1; (K is desired number of scenarios)
        for each vulnerable link (a.k.a. bridges)in network
            # generate a uniform random number Ua ranging from 0 to 1
            # determine the damage state that Ua  falls within
            # determine associated capacity and free flow speed reduction
        end
            # perform dynamic traffic assignment and determine the user
            equilibrium flow and network total travel time
            # calculate the increase in network total travel time compared to
            the base condition (without any damage to the network)
    end
output scenario_result
```

Figure 1 Pseudo code for disruption scenario simulation.

Modeling Network-wide Impact of Links Damage

It is critical to benchmark and gain a thorough understanding of how transportation systems (i.e. the links) are used under various disruption scenarios. Establishing knowledge about critical transportation links is important for two main reasons. First, the critical links identified can be given high priority for pre-disaster preparation and post-disaster cleanup. Second, it will help identify the potential communities vulnerable to disruption and network isolation when critical links are severed. We pursue a handful of possible disruption scenarios by means of computer simulation. The effort can help unveil how insidious certain links can be.

The Monte Carlo simulation ensures that for each scenario, the probability of link damage is estimated. The computer simulation that the result feeds into, enables the failure frequency of the entire roadway network to be evaluated for identifying the most critical links. As mentioned earlier, the computer simulation will generate for each scenario the network Average Travel Time (ATT). Average Travel Time Increase (ATTI) is further determined by comparing the simulation output with the average travel time of base condition (no damage to the network). ATTI is measured as:

$$ATTI_i = ATT_i - ATT_{base} \tag{1}$$

where $ATTI_i$ is ATTI for i^{th} scenario, ATT_i is ATT for i^{th} scenario, and ATT_{base} is ATT for base condition of the network (network works at full capacity). Regression analysis is performed to quantify the impact of links' capacity reductions (damage state) on network ATTI. The first assumption of the classic linear regression model specifies that the functional form of the relationship to be estimated is linear, however this assumption can be violated when linear functional form is used as an approximation to a non-linear functional form. Network disruption modeling is an example of such case since the functional form of the relationship between link capacity reduction and ATTI is unknown *(39)*. Following equation represents ATTI model as a function of vulnerable links' capacity reductions:

$$ATTI_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \beta_n X_{ni} + \varepsilon_i \quad (2)$$

where $X_{1i}, X_{2i}, \dots, X_{ni}$ are the capacity reductions for links' 1, 2,…, n in the i^{th} scenario, and ε_i is error term. $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients associated with the independent variables X_i, which also indicates the impact of the specific links' capacity reduction on ATTI.

APPLICATION

Study Network

The Salt Lake County's transportation network in the State of Utah is used to demonstrate our analytical method. The study network is prone to liquefaction-induced ground failure due to seismic events. The likelihood of earthquake hazard in the region increases the probability of lateral spread deformation. Lateral spread deformation is not generally life threatening; however, it can cause serious damage to transportation infrastructures, particularly bridges. The 1964 Alaska earthquake is an example. 266 bridges and embankments were damaged to varying extent due to seismic shaking, lateral displacement, fractures, etc. just to name a few, resulting in a total of $80 million of repair the Alaska Railroad and Highway *(1, 2)*.

For the purpose of this study, all the bridges in the study network are geocoded and treated as potential links that could suffer substantial damage after an earthquake. Zero damage probability is considered for other links. Note that the damage type associated with liquefaction event is not life threatening, it is therefore expected that most of people will resume their daily activities within a short period of time and the travel demand pattern would not vary significantly. The simulated post-disaster scenarios thus assume that the network will reach a new user equilibrium with the damaged links and no transient state is considered.

Salt Lake County transportation network is modeled in NeXTA *(40)*. The studied transportation network consists of 13,951 nodes, 27,981 links, 2,313 zones (TAZs), and 574 bridges (links). Figure 2 shows all the bridges located in the study area. We used PM peak-hour origin-destination demand matrix for year 2015 obtained from Wasatch Front Reginal Council (WFRC). Ten iterations are performed to reach the user equilibrium condition for each scenario. 400 scenarios accommodating various probabilities of damaged bridges and capacity reductions are created via Monte Carlo simulation. It feeds into the NexTA simulation model to determine the average network time and link volume.

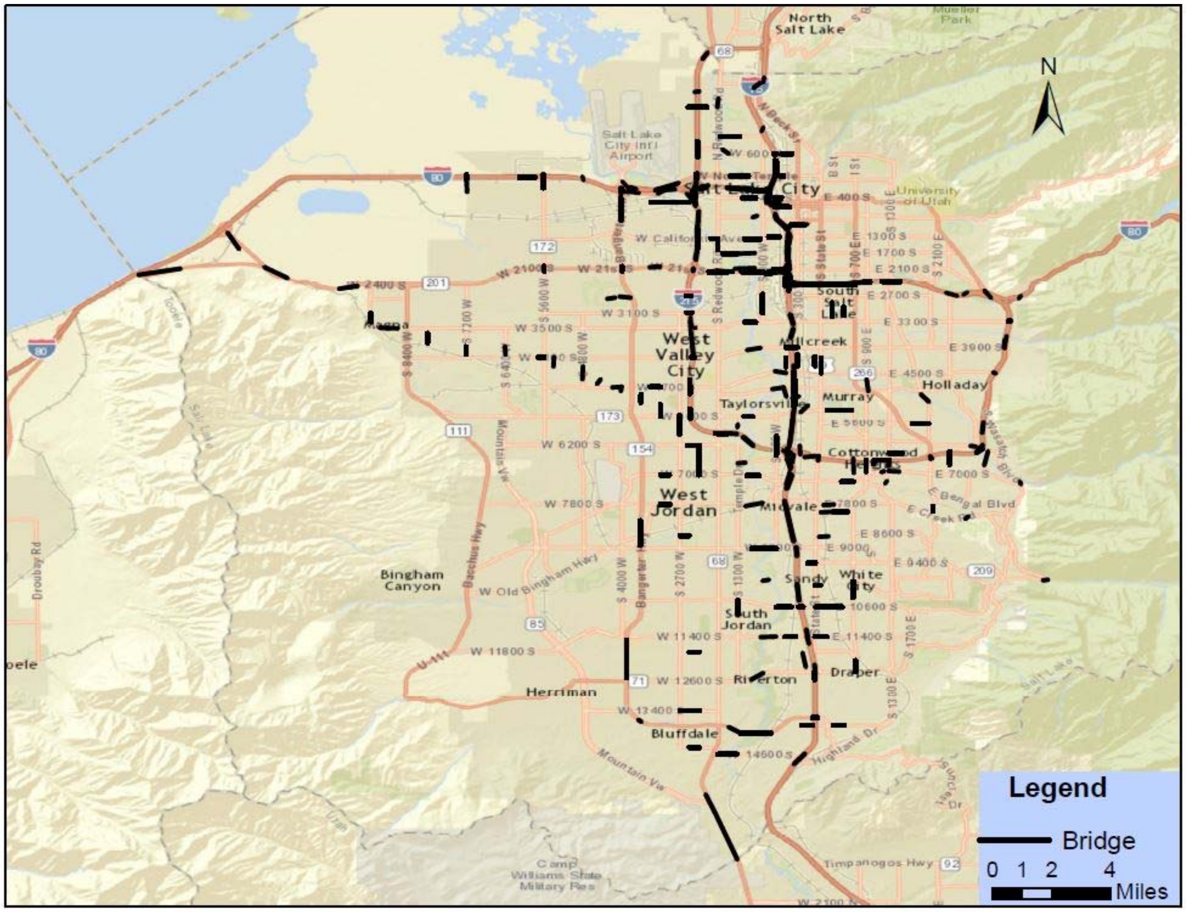

FIGURE 2 Vulnerable Links Located in Salt Lake County, Utah.

RESULTS

We focus on modeling the impact of M7.0 earthquake scenario event which is commonly used for seismic design and planning purposes *(37)*. Table 2 shows the simulation results. Each row in this table represents a scenario populated with estimated link capacity reduction and the resulted network ATTI. Of the 400 simulations, average network travel time increase is approximately 8.9 minutes/vehicle, a 70% more increase in travel time of the base scenario (12.5151 minutes/vehicle) where no link capacity reduction occurs. It is thus confirmed that travelers would encounter significant travel delay upon such earthquake events.

TABLE 2 Simulation Results

Scenario	Proportion of Links' Capacity Reductions									
	L1	**L2**	**L3**	**L4**	**L5**	**L6**	**…**	**L573**	**L574**	**ATTI (min)**
1	1	1	0	1	1	0	…	1	0	8.6043
2	1	0	1	1	0	0	…	0	0	9.7458
3	1	1	0	0	1	0	…	0	0	8.6729
4	0	0	1	0	0	0	…	0	0	8.3941
5	1	1	1	0	0	0	…	0	0	7.6269
6	0.5	1	0	0	0	1	…	0.5	0	7.4727
7	0.5	1	0	0	0.25	0	…	1	0	6.9271
8	0	0	0	0.25	0	0	…	0	0.5	7.6236
9	0.5	0	0	0	0.5	0	…	0	0	7.0431
10	0	0	0	1	0	1	…	0	0	8.2428
11	1	1	1	1	1	1	…	0	0	11.8508
12	1	1	0	1	0	1	…	0	0	10.1234
13	0	1	0	0	1	1	…	0	0	8.2439
14	0	0	0	0	1	1	…	0	0	8.8691
15	0	1	1	1	1	0	…	1	1	8.5232
16	0	0	0	0	1	0	…	0	0	7.1552
17	0	0	1	0	0	0	…	0	1	8.3316
18	1	0	1	0	0	0	…	0	0	8.9537
19	1	0	1	0	1	0	…	0	1	7.0527
20	1	0	0	0	0	0	…	0	0	7.6702
…	…	…	…	…	…	…	…	…	…	…
400	1	1	1	0	1	0	…	0	0	10.0236

Figure 3 shows the ATTI against capacity disruption level. Capacity disruption level is defined as the sum of all links' capacity reduction ratio (as shown in Table 2 for each scenario). Although with a general ascending pattern, the highest network ATTI does not occur at the highest disruption level. This indicates the possibility that a combination of bridges disruption (though less severe) might have more profound impact on the network travel time. Regression analysis is further conducted to identify those links or a combination of links. The optimal model is identified after eliminating the insignificant variables and unrealistic coefficients.

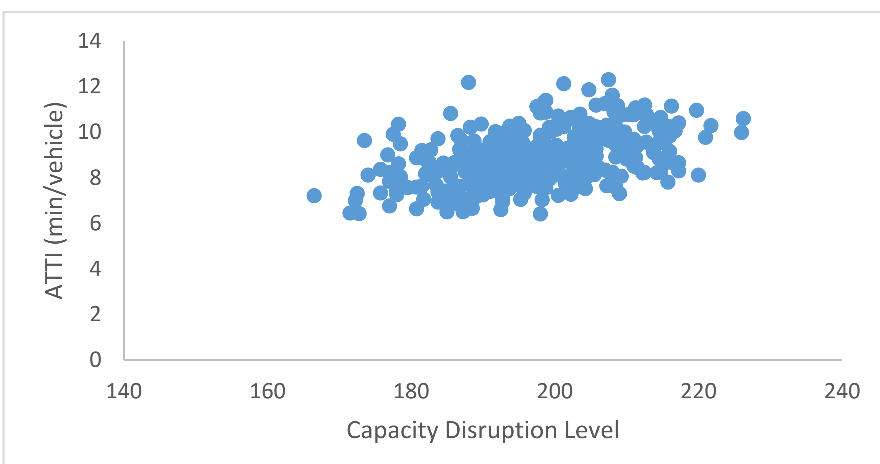

FIGURE 3 Change in Average Network Travel Time as the Capacity Disruption Level Changes.

Table 3 shows the result of the optimal linear regression model. All independent variables are statistically significant at 80% confidence level and the model shows excellent goodness-of-fit.

TABLE 3 Final Model Specification

R-squared = 0.99

Adjusted R-squared = 0.92

Link ID	Coefficient	Std. Error	P> |t|	Link ID	Coefficient	Std. Error	P> |t|
L332	0.546	0.091	0	L554	0.218	0.089	0.015
L232	0.503	0.094	0	L218	0.218	0.091	0.017
L185	0.488	0.095	0	L461	0.213	0.102	0.038
L428	0.468	0.098	0	L517	0.209	0.096	0.03
L54	0.392	0.101	0	L178	0.203	0.090	0.025
L211	0.384	0.103	0	L231	0.203	0.090	0.024
L204	0.382	0.091	0	L466	0.202	0.094	0.033
L390	0.378	0.105	0	L249	0.200	0.087	0.022
L533	0.372	0.091	0	L569	0.197	0.098	0.045
L516	0.363	0.093	0	L364	0.188	0.089	0.035
L92	0.358	0.091	0	L134	0.187	0.092	0.043
L31	0.354	0.095	0	L565	0.185	0.093	0.047
L56	0.345	0.097	0	L351	0.184	0.102	0.072
L562	0.341	0.091	0	L395	0.181	0.088	0.041
L214	0.335	0.091	0	L200	0.179	0.086	0.038
L427	0.329	0.093	0	L557	0.179	0.090	0.047
L41	0.323	0.111	0.004	L372	0.179	0.089	0.046
L403	0.306	0.098	0.002	L228	0.175	0.095	0.067
L21	0.299	0.092	0.001	L105	0.175	0.092	0.058
L52	0.295	0.091	0.001	L154	0.174	0.097	0.073
L267	0.293	0.090	0.001	L280	0.174	0.099	0.079
L449	0.292	0.089	0.001	L62	0.173	0.089	0.052
L509	0.283	0.093	0.003	L320	0.171	0.092	0.064
L518	0.280	0.100	0.005	L510	0.167	0.091	0.066
L152	0.276	0.087	0.002	L514	0.167	0.090	0.064
L502	0.272	0.091	0.003	L522	0.167	0.091	0.067
L29	0.271	0.097	0.006	L39	0.165	0.095	0.083
L530	0.264	0.089	0.003	L187	0.157	0.089	0.08
L28	0.257	0.090	0.004	L376	0.157	0.088	0.075
L197	0.256	0.104	0.015	L130	0.156	0.089	0.082
L513	0.254	0.091	0.005	L53	0.148	0.090	0.101
L233	0.249	0.089	0.005	L72	0.142	0.091	0.122
L173	0.248	0.086	0.004	L397	0.139	0.087	0.113
L55	0.240	0.101	0.018	L195	0.136	0.089	0.126
L198	0.239	0.096	0.013	L369	0.136	0.092	0.141
L325	0.236	0.091	0.01	L420	0.135	0.089	0.128
L244	0.234	0.086	0.007	L186	0.132	0.093	0.156
L174	0.229	0.089	0.011	L473	0.132	0.093	0.155
L373	0.226	0.090	0.013	L86	0.132	0.094	0.165
L501	0.226	0.092	0.015	L365	0.130	0.093	0.162
L230	0.220	0.090	0.015	L153	0.130	0.099	0.193
L77	0.219	0.092	0.017				

Note that the capacity reductions of 83 links have substantial impact on total network travel time. The larger the estimated coefficient of each variable (bridge), the higher impact of that link on networks ATTI.

In the following analysis, we are distinguishing the links between vulnerable, critical, and congested. Vulnerable links, as mentioned in the *Methodology* section, are all the bridges within Salt Lake County that are susceptible to liquefaction-induced damage. The *most vulnerable links* represent links where their probability of experiencing severe damages (collapse and extensive damages) exceeds 30 percent amongst the 400 scenarios generated. *Most critical links* refer to the top 20 links whose coefficients are among the highest in the regression model. *Most congested links* are those that their v/c ratio (volume to capacity ratio) exceeds 0.8 in the base condition.

Table 4 shows the top 20 most critical links across Salt Lake County transportation network. The rank shows in descending order from the most to least critical. As shown in the column of *Base Condition Volume*, these links do not necessarily carry large traffic volume. However, few alternative routes are available in case disruption occurs to those links. As illustrated in Figure 4, some of the most critical links are located on reliable alternative routes (reliable routes are those consisting of minimum number of links with severe damage probability) that carry detouring traffic.

TABLE 4 Ranking of the Most Critical Bridges across Salt Lake County Transportation Network

Ranking	Link ID	Road Name	Link Type	Length (mi)	Capacity (vph)	No. of Lanes	Speed Limit (mph)	Base Condition Volume (vph)
1	L332	SR-201	Freeway/lower capacity	0.29	5800	3	67	6000
2	L232	Meadow Br	Minor arterial	0.37	1500	2	31	1250
3	L185	CD Road	Freeway/system loop ramp	0.25	1800	1	40	800
4	L428	I-15	Freeway/lower capacity	0.25	5800	3	67	6820
5	L54	4100 South	Principle arterial	0.07	1700	2	31	1030
6	L211	CD Road	Freeway/high speed CD	0.68	3500	2	55	810
7	L204	9000 South	Principle arterial	0.63	1700	2	32	1310
8	L390	I-215	Freeway/higher capacity	0.5	6700	3	67	4570
9	L533	I-15	Freeway/higher capacity	0.26	8000	4	67	2600
10	L516	Creek Rd	Major collector	0.12	700	1	30	300
11	L92	3300 South	Principle arterial	0.29	2400	3	32	1300
12	L31	CD Road	Freeway/high speed CD	0.66	3500	2	55	580
13	L56	500 West	Major collector	0.5	600	1	24	80
14	L562	I-15	Freeway/higher capacity	0.41	6400	3	67	2600
15	L214	South Jordan	Minor arterial	0.39	1700	2	27	1840
16	L427	I-215	Freeway/higher capacity	0.27	4900	2	67	3770
17	L41	5600 West	Minor arterial	0.16	1600	2	36	1940
18	L403	I-215	Freeway/higher capacity	0.6	8400	4	67	7550
19	L21	North Tem	Minor arterial	0.48	2200	3	31	600
20	L52	2100 South	Minor arterial	0.51	1500	2	31	10

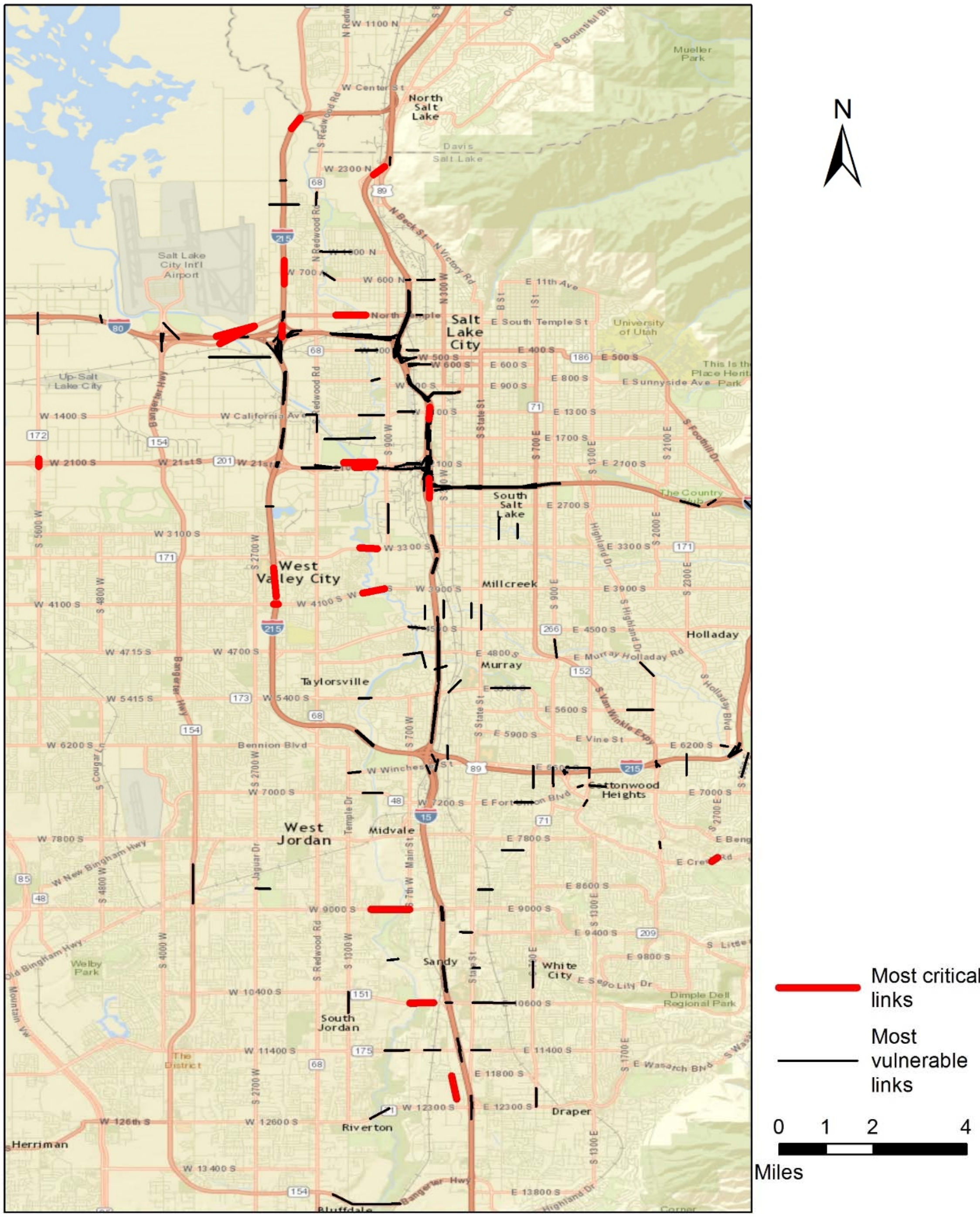

FIGURE 4 Map of Top 20 Most Critical Bridges across Salt Lake County Transportation Network.

As an example, consider the section of I-80 illustrated in Figure 5. In case of I-80 closure, North Temple Street can be used as an alternative route. There are three vulnerable links on North Temple Street and several vulnerable links on I-80. The high number of vulnerable links on I-80 increase its closure probability. Fortification of an individual link along I-80 might not improve the resilience of I-80 given that the failure of other links marked in Figure 5 might as well prevent its functionality. Consequently, in order to guarantee the operation of I-80 several links need to be fortified while only three links are required to keep North Temple Street functional.

The linear regression can identify this by following explanation. Assume that failure of both I-80 and North Temple Street together will increase the ATT (ATTI) by x minutes, then impact of each bridge failure in I-80 and North Temple Street simply estimating will be x/15 and x/3 respectively. Thus the North Temple Street links will rank higher in criticality.

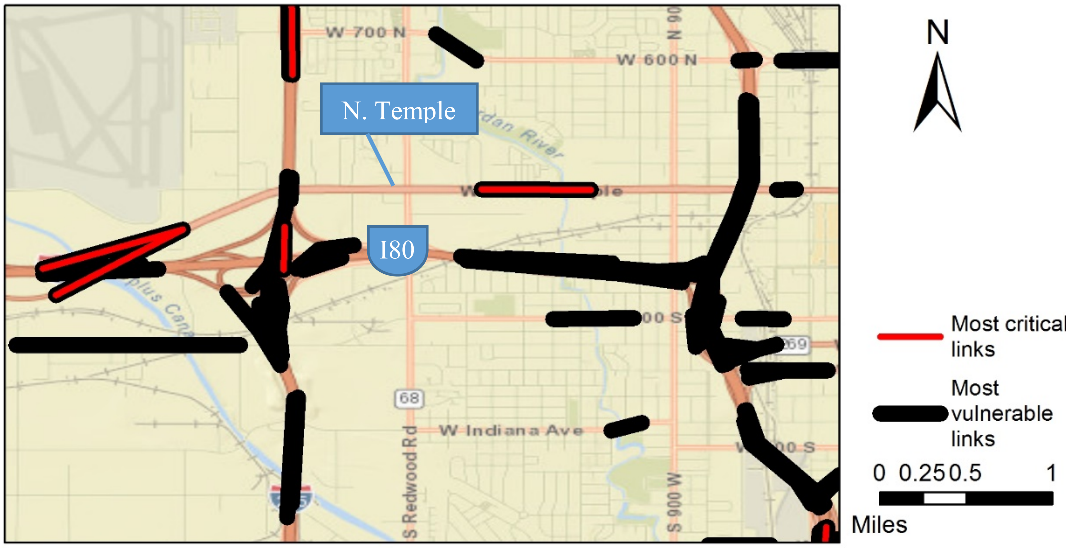

Figure 5 Map of Most Critical Bridges Located on North Temple Street.

Results Interpretation

Figure 6 depicts the map of critical links identified by linear regression model. As shown in this figure, almost for all of the critical bridges there is a high probability of severe damages and most of them have experienced congestion in base condition. Four different link categories are specified to interpret the results of this study. Categories are defined based on the similar characteristics that set of links share together. The first category includes links that connect main freeways (I-15, I-80, and I-215) and provide access to the downtown area. The second category consists of set of links that provide connectivity in the network. Network Connectivity refers to how well connected the network is regarding the number of links and alternative routes connecting network nodes. The high damage probability of all the links in the set will affect the connectivity between parts of network in most of disruption scenarios. Third category consists of freeway links that carry large traffic volume but are not identified as critical links. The last category are links that are located on routes which are providing reliable alternative routes for freeways. These four categories are discussed in detail as follows.

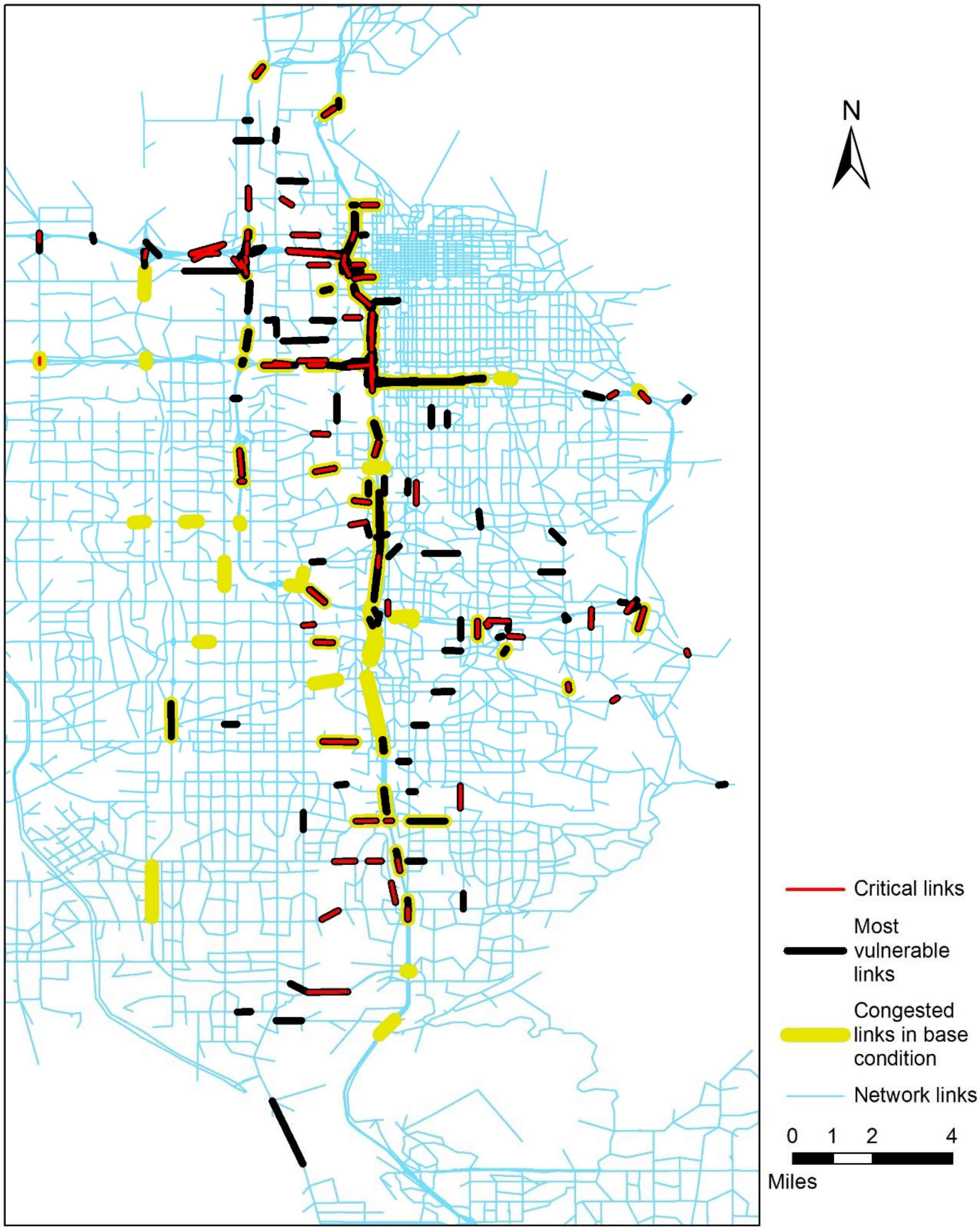

FIGURE 6 Map of Critical Bridges across Salt Lake County Transportation network.

Category I

Figure 7 illustrates the first category of critical bridges. Most of these links are located over the interchanges that connect main freeways and provide access from/ to the downtown area. These links also carry a large traffic volume and in the case of their disruption there are a few alternative routes that can accommodate this demand. High vulnerability of exit and entering ramps in this part of the network restrains available alternative routes. Furthermore, the high vulnerability of exit and entrance ramp affects the large portion of freeways functionality.

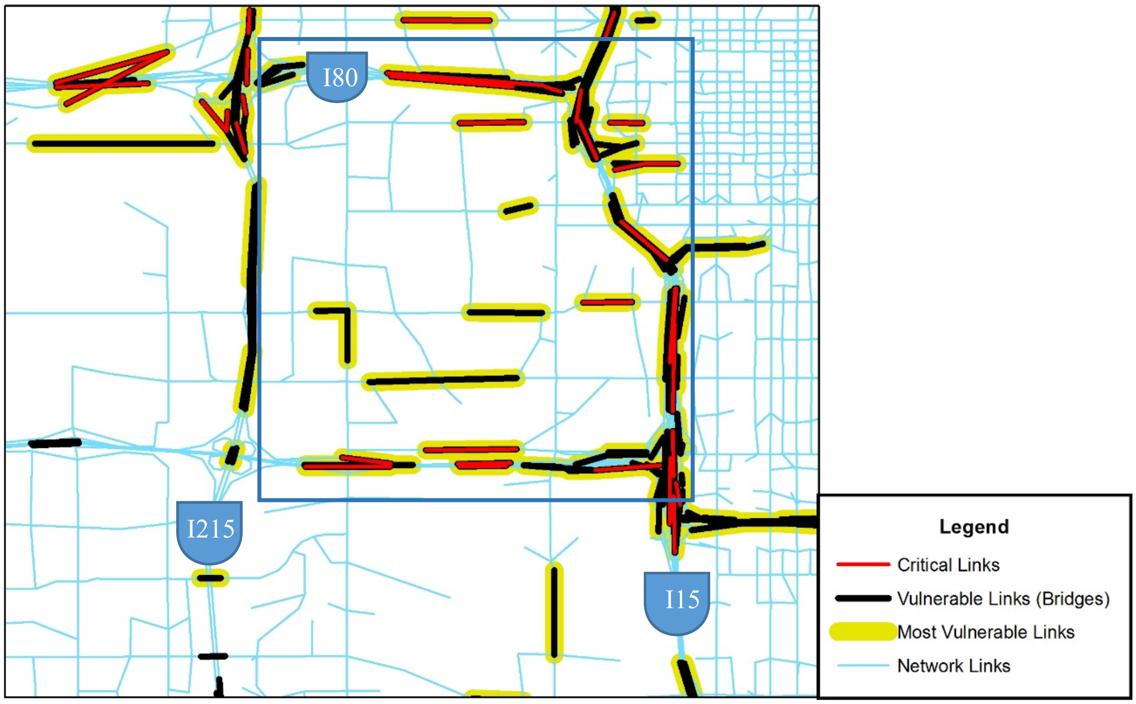

FIGURE 7 Category I of Critical Bridges in Salt Lake County Transportation Network (highligted in box).

For instance, the closure of one or two links can paralyze the entire freeway. Under these circumstances, travelers have to exit freeway and take local roads which have fewer speed limit and capacity. Due to its close vicinity to the downtown area, the alternative routes are already congested which will result in extensive additional load on the already congested routes. Consequently, a large portion of travelers will experience more delay compared to the base condition and this will result in substantial increase in network total travel time. Therefore, the criticality of this category can be explained by their high damage probability, large traffic volume, and unavailability of reliable alternative routes.

Category II

The second category consists of sets of links that provide the connectivity between different parts of the network. Figure 8 exhibits this category of links. Failure of these links in each disruption scenario will reduce the connectivity and increase travel time between less connected communities of the network. In case of such failure, travelers have to take longer alternative routes. Most of the available alternative routes are either congested or do not have enough capacity to carry detouring traffic. Movement of detouring traffic toward these alternative routes causes the accelerated deterioration of these routes. Consequently both regular users on their usual shortest path and the detouring traffic would experience more delay. It is worth mentioning that the majority of past studies are unable to identify this category as critical links since they mostly focus on the individual impact of each link removal on network performance and most of these bridges do not carry a large traffic volume in normal condition. Therefore, their individual removal from the network do not affect network total travel time significantly but the set failure have serious impact on network total travel time. Considering the combination of bridge failure enables us to identify these bridges as critical.

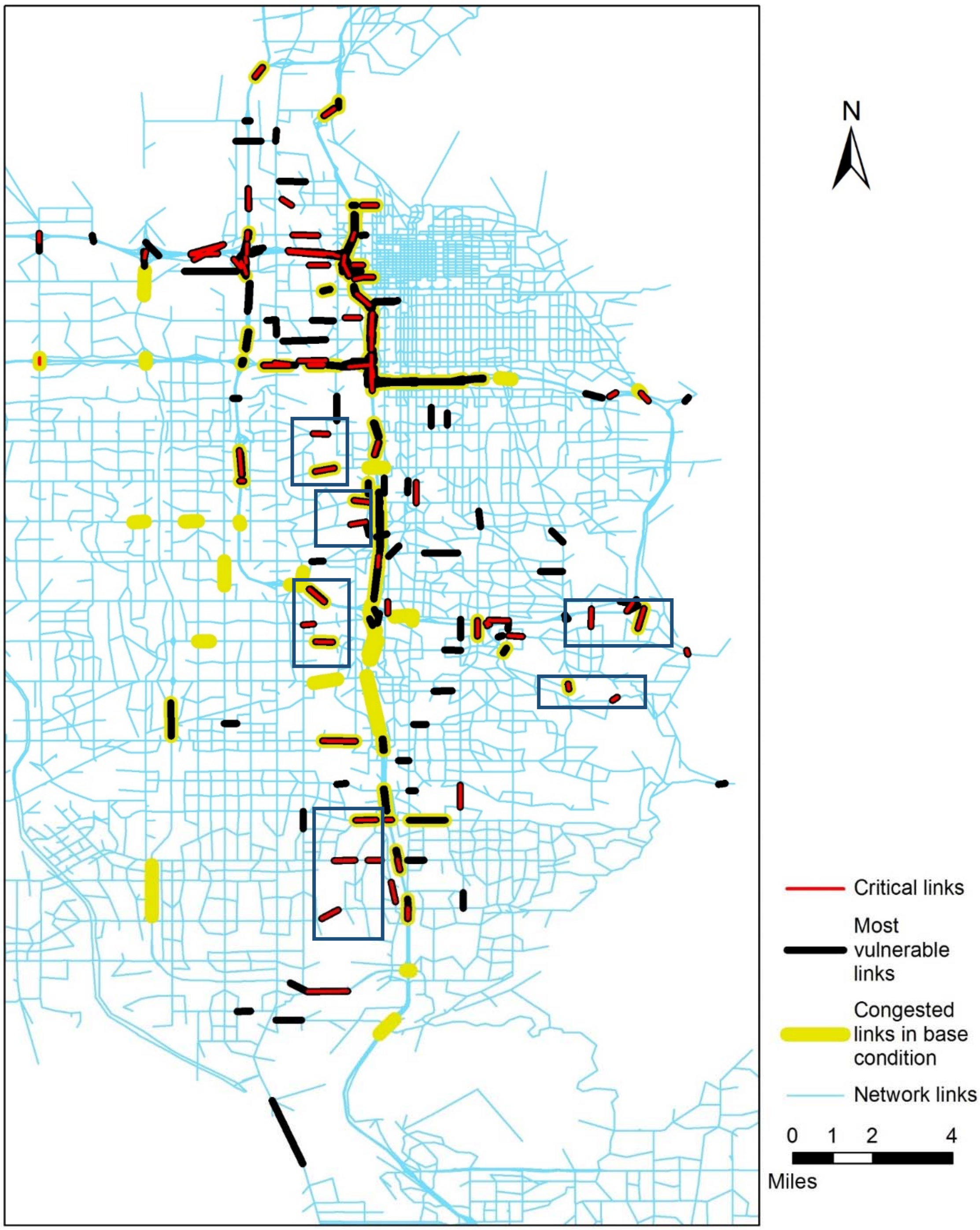

FIGURE 8 Category II of Critical Bridges in Salt Lake County Transportation Network (highligted in boxes).

Category III

As shown in Figure 9, there are also other links that have high damage probability and carry large traffic volume but they are not identified as critical links. In case of these links disruption, there are reliable alternative routes that can accommodate detouring traffic volume. Availability of reliable alternative routes substantially attenuates impact of these links' disruption on ATTI. However, the past studies' method may give higher importance to these links compared to the second category discussed above. That's because previous studies do not consider the combination of bridges disruption.

Category IV

There are some reliable routes across the network that can be used as alternative routes in case of main routes closure. The *Category IV* consists of links that are located on these reliable alternative routes. Failure of only one link from this category of links will cause the closure of a valuable reliable alternative route. Our results revealed that this category of critical links have the highest impact on network total travel time.

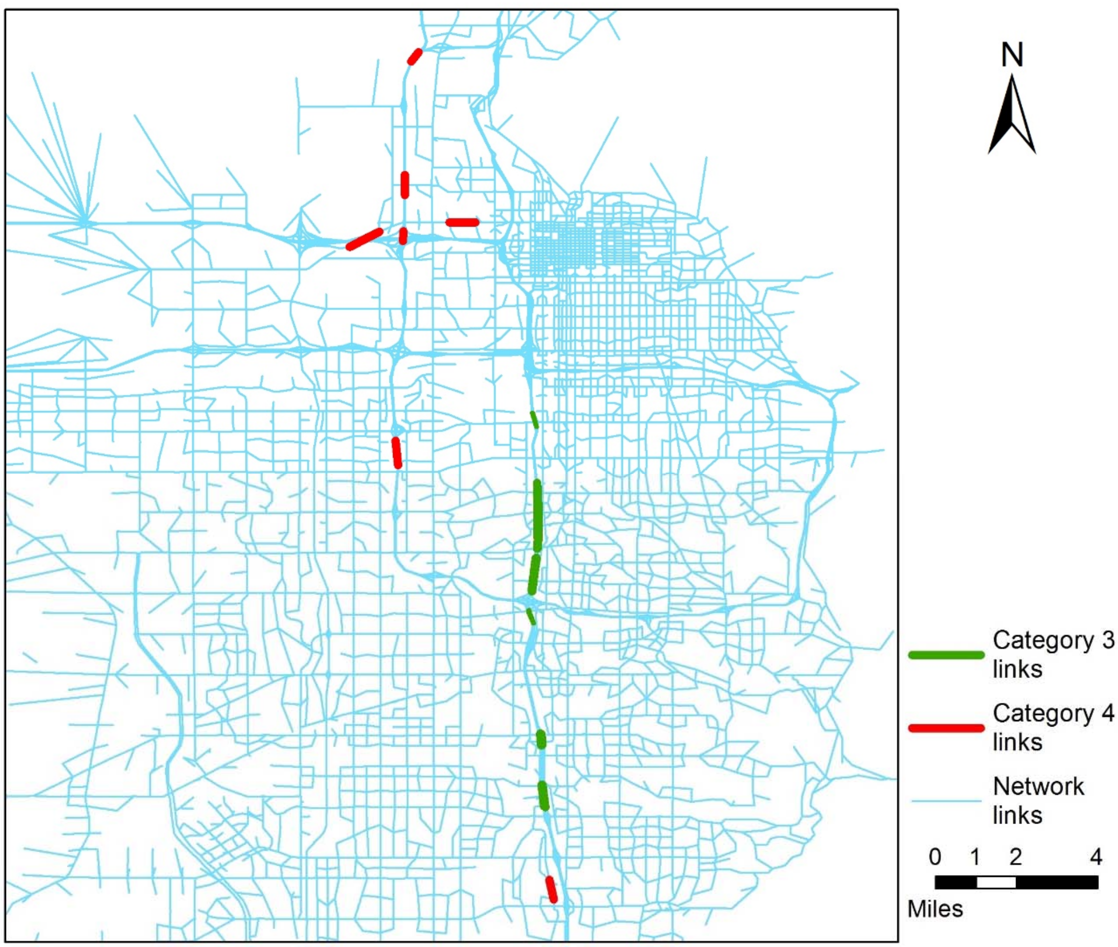

FIGURE 9 Map of Category III and IV Links across Salt Lake County Transportation Network.

CONCLUSION

The main objective of this study was to propose a methodology for identifying most critical links in the transportation network and prioritizing them for pre-disaster retrofit efforts. We maintain that it's crucial to consider both probability and consequence of each link damage, so critical links are those that have high severe damage probability and their damage have significant impact on network overall performance. We also mentioned that it's essential to consider the combined effect of links' disruptions on network performance measures. Moreover, a probabilistic approach were utilized to take the uncertainty about the disruption scenario into account. Therefore, by considering links' damage probabilities and the combination of links' disruptions the major shortcomings of previous studies were addressed.

We applied our method to a real size transportation network, Salt Lake County network, to identify the most critical bridges in the network and prioritize them for pre-disaster retrofit efforts. Monte Carlo procedure was utilized to simulate 400 disruption scenarios that can occur after a M7.0 earthquake. Then, the results of Monte Carlo simulation were used to develop the optimal linear regression model. Our results reveals that the damage of 83 bridges have significant impact on network overall performance. These critical bridges do not necessarily carry large traffic volume but in case of their disruption there are a few alternative routes that can carry detouring traffic. In order to interpret the results, we introduced four categories of links. The first category consists of links that carry large traffic volume and provide main access to the downtown area. In the case of these links' disruptions, there are a few reliable alternative routes that can carry such a large traffic volume. The second category includes sets of links that provide connectivity between different parts of the network. In the case of each set failure much longer alternative routes are available for travelers which can tremendously increase road users' travel time. Third category consists of freeway links that carry large traffic volume but they are not identified as critical links. Most of past studies give higher importance to this category of links than second category. Availability of reliable alternative routes in case of these links failures is the reason why they are not identified as critical links. The last category of links are vulnerable parts of reliable routes that provide alternative routes for freeways. Our results reveal that these links have highest priority for fortification efforts.

The proposed method can be easily applied to different transportation networks regardless of scale, topology, and the type of disaster that might impose disruption. We used usual PM peak hour demand for traffic network modeling. Yet in case that more information about the change in demand pattern is available, modified demand matrix can be used for simulating various disruption scenarios. Moreover, we assumed that after a short period road users reach a new equilibrium and no transient state of network is considered but in order to make simulation more realistic day-to-day traffic modeling can be conducted. We also assumed that the disruption of each link does not have any impact on performance of other network links but in reality when a bridge collapses operation of all the links crossing under the bridge will be affected.

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