SECOND EUROPEAN CONFERENCE ON EARTHQUAKE ENGINEERING AND SEISMOLOGY, ISTANBUL AUG. 25-29, 2014

SEISMIC RESILIENCE ASSESSMENT OF HIGHWAY NETWORKS: A TOPOLOGY-BASED APPROACH

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ABSTRACT

A topology-based approach has been used to measure the resilience of a highway network to extreme events of random nature. The transportation network is represented as a combination of links and nodes. The fundamental topological properties of a network can provide resilience measurements appropriate to comprehend the preparedness and functionality of an infrastructure system in the face of various hazards. The principles of graph theory are employed to determine a range of measures from the average node degree to the clustering coefficients. Topological properties will be exclusively relied on for resilience representation in this study, as they provide a simple and established characterization of the network and can be correlated to resilience properties. Towards this goal, the case study focuses on highway transportation networks of the San Francisco Bay Area and introduces an approach to determine the topological properties of the highway network. The measures are then applied to the definition of resilience, allowing for a quantification of network resilience from topological graph properties.

INTRODUCTION

With the awareness of extreme events and disasters growing with the continued development of societies, researchers have recently began to place a strong emphasis on the *resilience* of infrastructure systems, a concept defined as the ability of the system under consideration to withstand, adapt to, and rapidly recover from various effects of disruptive events (Turnquist and Vurgin, 2013). Among various infrastructure systems, those which comprise civil infrastructure (e.g., transportation networks, water distribution systems, and power transmission lines) are universally recognized as especially critical due to their societal importance. The ability to evaluate the resilience of infrastructure networks becomes vital to reduce susceptibility to failure. It is thus paramount to holistically assess the components of civil infrastructure and prepare for the consequences of failure or disruption in their normal services. This is in addition to all the preparations that must be made for prompt response and emergency recovery to maintain resilience of the community after extreme events.

Exploring investigations of both the concept of resilience and the effects of extreme events on civil infrastructure has revealed a variety of analysis approaches. For instance, Alipour (2010) evaluated the lifetime resilience of highway networks considering the effect of component aging. Shafei et al. (2012 and 2013) developed comprehensive models for predicting corrosion induced deterioration in reinforced concrete members. Alipour et al. (2010 and 2013) used these predictive models to estimate the seismic capacity loss of the bridges in a highway network. Furtado and Alipour

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(2014a) integrated the transportation network and regional economic models to measure the resilience in terms of direct and indirect costs associated with failure of bridges, they also proposed prioritization methods for bridge repair to enhance the functionality of the networks after earthquakes (Furtado and Alipour 2014b). While there have been attempts to qualitatively report resilience, at the current time, there is no efficient method to quantify resilience with regards to natural disasters nor an appropriate way to compare the resilience of different civil infrastructure systems (Simonovic, 2012). Although compiling the many forms and studies of resilience can result in a better understanding of the concept, the ubiquity of the concept can become a barrier in standardizing its measurement. In fact, some authors are willing to propose there is no possible way to measure resilience with a single number, but that it must be represented on a multi-dimensional platform with several contributing factors (Haimes, 2009).

Holling (1973) defines resilience as a parameter that quantifies a system's ability to exist while changes in its environment or conditions are assimilated. As the first author to introduce the idea of resilience in an academic, scientific setting, Holling provided a base on which evolutionary biologists would build for tens of years. After reviewing a range of definitions, including ecology-, economy- and hazard-based, a number of characteristics are common to the general definition of resilience. The concept of adaptability is used in varying ways, but the root of the quality remains the ability to change in the face of an extreme event. The speed and completeness of recovery is mentioned in a number of sources, whether referring to a structure or economic market. Absorptiveness, and the ability of a system to reduce and adjust to shock, is another common part of the definition of resilience. In total, these compose four important "abilities" of a system which are used to measure resilience: ability to anticipate, to absorb, to adapt and to recover (Francis et al., 2004). Additionally, across disciplines, the idea of resilience almost always includes both pre-event and post-event tasks.

One of the easiest parameters to collect pre- and post-event is the size of the largest cluster of nodes. The next logical measure is that of the longest or average shortest path between nodes, showing the increase of travel time within the network. As nodes are removed, the network gradually separates into completely disjointed clusters. With this growing disjointedness follows an increase in the shortest path between two network nodes, a measure especially relevant to the study of traffic and transportation. Holme et al. (2002) brings an important point about network topology that challenges the accepted significance of node degree value. While nodes with the highest degrees are vital, nodes with small degrees may connect two important clusters of a network, acting as bridges. These should not be overlooked in evaluating resilience. By this logic, the relevance of measures of betweenness centrality has evolved. Betweenness centrality, like node degree, is specific to each node and depends on the number of shortest paths within the network which travel through the considered node. One would expect that the node with the most degrees has the highest betweenness, but this is disproved by the nodes which form important network bridges.

Real networks function and grow under what are often less than ideal circumstances and environments. Albert et al. (2000) attribute this resiliency to the inherent redundancy built into these complex systems and refer to it as error tolerance. Blume et al. (2011) studied the resilience of networks to cascading failures, defined as failures which spread from node to node across the network. Examples of cascading failures are readily apparent in power grids and, perhaps most obviously, among human populations during the spread of disease. The approach used to evaluate cascading failures is largely based on the topological properties of a network; different structures of networks tend to behave differently when undergoing cascading failures.

A network of nodes and links is used to represent the transportation network in this study. The links serve as roadways and the nodes are locations of destinations and points of connectivity. Maintaining order and functionality in civil infrastructure after a disruptive event is only possible if the most important nodes and links are identified. With this knowledge the network can be improved and developed to withstand such events. By evaluating the topological properties of the network, quantifications of resilience are found that measure the preparedness of an infrastructure system to extreme events. The topological properties used are derived directly from the fundamental theories of graph theory to achieve consistency and reliability. While graph theory encompasses levels of analysis other than topological ones, topology measures translate best to real networks and their resilience.

FUNDAMENTAL PROPERTIES OF A NETWORK FOLLOWING GRAPH THEORY

Knowledge of the most fundamental concepts of graph theory is necessary to investigate the topological parameters of a network. For this reason, an overview of essential terms and definitions in graph theory will be discussed. Graphs are composed of two types of elements--links (edges) and nodes (vertices)—and can be uniquely defined by the set of links and nodes it contains. The connections and locations of nodes and links determine the majority of identifying properties of the graph.

Several properties are actually graphs in themselves--collections of links and/or nodes of the main graph. These, or any defined subsets of graph elements within a larger graph, are called *subgraphs*. In highway network studies, properties of a *path* between two nodes are of special importance. A path is an ordered sequence of links necessary to travel from the origin node to the destination node; the length of a path is the number of links it includes. *Distance* is expressed as a length, but it is always the length of the *shortest path* between two nodes. If there is no path connecting two nodes, the distance is defined as infinite.

Topological graph theory is based on the physical layout, or structure, of the graph and relies on several measures of connectivity. Topological graph parameters are sometimes combined with those measuring network flow as topology-flow effects. Networks and graphs are two different terms to describe the same concept, although networks are usually examples of graph systems that exist in reality. Connectivity, a reflection of the adjacency and ease of flow between nodes via links, is closely tied with the intra-dependencies of the network. There are various levels of connectivity, but the highest exists is that of a complete graph, where for every pair of nodes there exists a link between them. For a graph to be connected at all, at least one pair of its nodes must be linked by a path. When evaluating the response of a network to a node or link failure, the interruption of flow or failure of paths is contingent on the connectivity. If a link fails, flow may still be possible between two nodes if there are other available paths along connected nodes. Thus maintaining a certain level of connectivity is necessary to preserve the functionality, or operability, of the network.

Node degree is a network measure which compares the number of nodes to the number of links per node. For one node, the degree, $d(v)$ is defined as:

$$\mathrm{d(v)} = |\mathrm{E(v)}| \tag{1}$$

where $|E(v)|$ is the number of links at node v. The average degree of the network is simply the total number of degrees in the network summed over all nodes, divided by the number of nodes in the network.

$$d(G) = \frac{1}{|V|}\sum_{v\in V} d(v) \tag{2}$$

Clustering Coefficients are found to quantify the local clustering of graph elements into *neighborhoods* and are a measure of local connectivity. A neighborhood of a vertex v is denoted $\Gamma(v)$ and is essentially a subgraph comprised of the nodes adjacent to v (excluding v).

$$\gamma_v = \frac{|E(\Gamma_v)|}{\frac{1}{2}d(v)(d(v)-1)} \tag{3}$$

In Eq.(3), $|E(\Gamma_v)|$ is the number of links in the neighborhood of v. The denominator is the number of possible links in $\Gamma(v)$. The value of the clustering coefficient, which is between zero and one, expresses the portion of neighbors of v that are connected.

Shortest path is especially relevant to studies of transportation systems. The flow of a highway or road network is the traffic which moves along its links, dependent on the trips taken by vehicles. Likewise, trips are dependent on origin-destination data as well as the shortest path between the origin and destination pairs. There are several methods for calculating the shortest path between two nodes, but most revolve around a similar basic procedure.

$$l_G = \frac{1}{n(n-1)} \sum_{i \neq j} d(i, j) \tag{4}$$

The variable n in Eq.(4) is the number of nodes in the network. Starting at one vertex, i, and all other nodes marked as unoccupied, the distances to every neighboring node by a link is marked. The algorithm moves to this set of neighboring nodes and considers the distances to the neighbors of the neighbors, marking each with a new distance. If a node can be reached with a shorter path, its marked distance is replaced with a smaller number. The "shortest" path is eventually found as all nodes of the network are evaluated to get from node i to node j.

Betweenness centrality is used to identify the most important, critical nodes to the network flow and is a measure of the centrality of a node. It is defined as:

$$b_v = \sum_{i \neq v \neq j} \frac{g(i,v,j)}{n(i,j)} \tag{5}$$

where $g(i,v,j)$ is the number of shortest paths from node i to node j that pass through v. The denominator within the summation represents the total number of shortest path from i to j. The longest distance from any node of a central node is that which is as small as possible. The betweenness centrality quantity can be compared for all nodes in the network to decide where to direct resources and make resourcefulness decisions. It essentially provides a measure from which to rank the network links and nodes according to their roles in topology and flow. By depending on the betweenness centrality quantity to rank nodes instead of other measures, like nodal degree, the possibility of missing important nodes that may form vital bridges between peninsulas or interstates is avoided. The ability to rank network elements is the first step in predicting response to the removal or failure of elements.

RESILIENCE CONTEXTUALIZATION

Resilience is characterized by a variety of factors which can be quantified by the parameters described in the previous section. Nodal and average degrees, which allow the determination of degree distribution, are crucial to the vulnerability of a network to nodal or link failure. The degree distribution across all nodes relates to the network robustness, or how well the network absorbs a shock without failure in service or functionality after an extreme event. By categorizing the degree distribution, specifically as homogeneous or heterogeneous, the level of damage after a catastrophic event can be estimated. Separately, the algorithm to calculate nodal degrees is often the first step in the calculations of other parameters, such as betweenness. The betweenness centrality measure underscores the importance of nodes relative to links in a network and becomes central to a discussion on network resilience. The removal of a node potentially affects several links, certainly all the links of which it is an end. The removal of a link, however, only affects the functionality of one link. Therefore, the failure of a network node is more harmful to network performance than the failure of a link. By ranking nodes based on betweenness centrality, the resilience of a network to extreme events can be quantified. Events that result in the failure of important nodes are clearly more devastating than those on nodes of lower importance.

Real networks are usually composed of several smaller networks, called clusters. Parameters specific to each cluster provide revealing information of the resilience and redundancy of a network, especially locally. In transportation networks, evaluating clusters allows for the efficient concentration of improvements and funds to the most needy network areas. The clustering coefficient is a measure of connectivity – specifically, how connected the network is locally. This is sometimes referred to as the "regularity" or "locality" of the network. For a grid-like network, a large clustering coefficient corresponds to a high average path length. In fact, however, most real networks have high clustering coefficients but low average path lengths. With regard to the factors of resilience, the clustering coefficient is best representative of redundancy. In preparing a network for disaster, policy makers would be better equipped to make decisions about the locations of resources and where more improvements could be made. With measures of graph parameters contextualized by factors relevant to resilience, the resilience of the network is better understood.

HIGHWAY NETWORK OF SAN FRANCISCO BAY AREA

To apply a topological graph theory approach in a resilience investigation, the highway system of the San Francisco Bay Area was condensed into a network of nodes and links. The network consists of 2,317 nodes and 14,823 links which compose the highway network (Fig. 1).

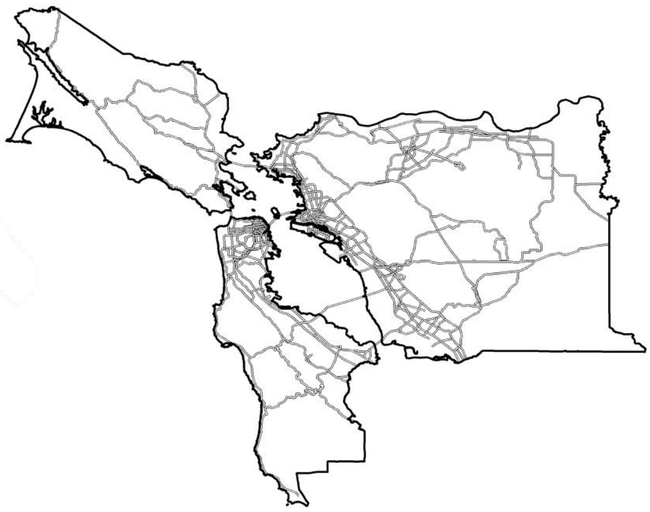

Figure 1. San Francisco Bay Area highway system

San Francisco was chosen as a case study because of its proximity to a hotbed of tectonic activity, the San Andreas Fault zone, and its growing civil infrastructure. Interestingly, its public transportation system does not span the Bay Area and its population relies heavily on vehicles and the highway network. While research is commonly concentrated on the susceptibility of structures to seismic activities or natural disaster, evaluating the resilience of a critical infrastructure system is paramount to the continued functionality of the Bay Area after possible extreme events such as earthquakes. For this purpose, the topological graph properties are determined using mathematical manipulations, as they would be calculated for any network.

To better understand the effects of an extreme event on the San Francisco highway network, a fraction of random links were removed to simulate a (non-targeted, random) extreme event. One of the simulations is graphically illustrated in Fig. 2. After each set of arbitrary links was removed, the network parameters were measured and recorded using Eqs. 1-5. The results illustrate the consequences of a random network failure and the effects of the fraction of elements removed on each network parameter.

Fig.4 presents the variation of average nodal degree across the network. The initial average nodal degree of the network was 12.8. As nodes were randomly removed, the average degree parameter linearly declined in a continuous trend towards zero. This is expected, as the removal of links is linear and is directly correlated to the degree of each node which decreases as adjacent links disappear or fail. The average degree is dependent only on the total number of links and nodes; the number of nodes remains unchanged by mathematical manipulations, so it follows the same trend as the number of remaining links. The error is also identical for each fraction of links removed, further confirming the minimal dependence of the average nodal degree. Although seemingly predictable, the decreasing average nodal degree represents the declining global connectivity of the network. If a sizable portion of links was suddenly removed or failed, the nodal degree would drop significantly and commuters would have far fewer possible routes to destinations.

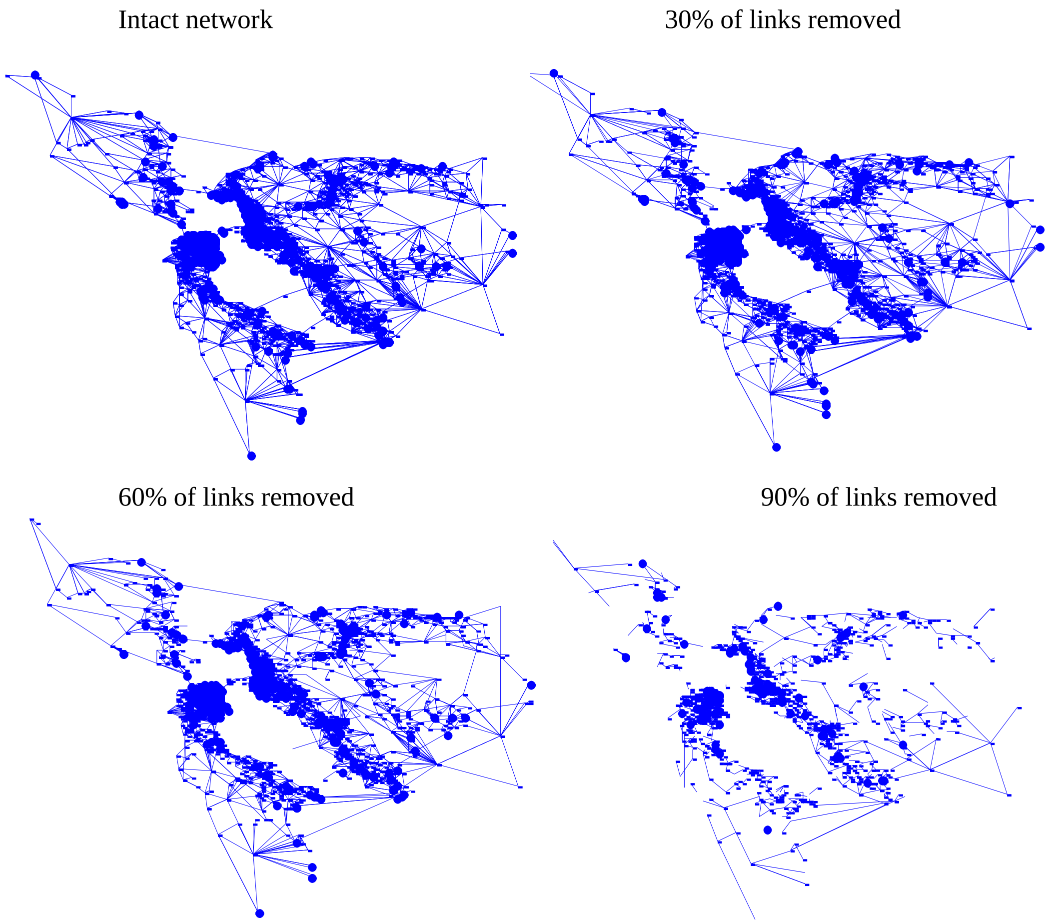

Figure 2. San Francisco network link removal

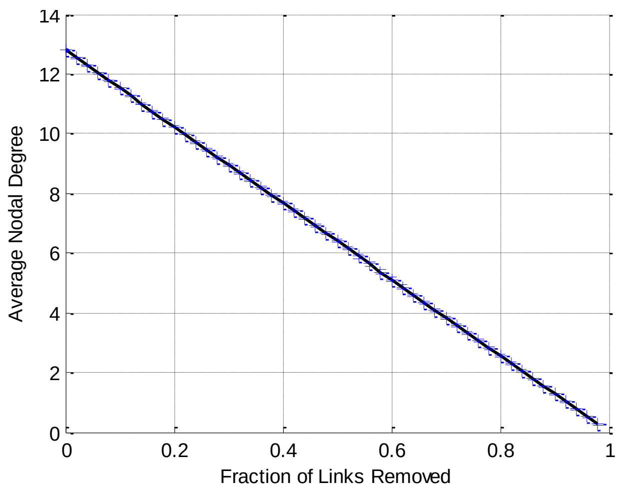

Figure 3. Effect of random link removal on average nodal degree

The clustering coefficient, a measure of local connectivity, is 0.054 for the intact highway network. As links are randomly removed, the value of the clustering coefficient follows the trend shown in Fig.4. By removal of approximately 0.14 of links, there is an immediate but brief increase in local clustering. This is mainly due to the formation of more defined clusters (i.e., neighborhoods), which occurs when a limited number of links are removed and is very likely to occur in a dense network like San Francisco Bay Area. For example, in a highly connected network, clusters of nodes and links may not exist; all nodes and links may simply be clumped into one large cluster. In this case, when a small portion of links is removed, more clusters start to appear and the clustering coefficient increases. However, as the number of removed links increases past a certain point, the clusters themselves start to disintegrate and the coefficient follows a decreasing trend towards zero. The decreasing portion of the curve is comparable to the linear slope of the average nodal degree (Fig. 3).

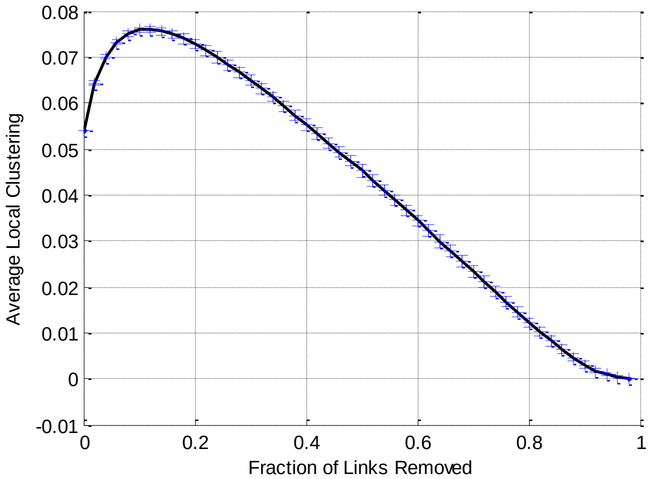

Figure 4. Effect of random link removal on average local clustering

The average betweenness centrality is a property of network that highlights the relative importance of nodes to network performance (Fig. 5). As with the average shortest path, the average betweenness centrality value steadily increases until approximately 50% of the links are randomly removed, at which point it rapidly declines. The increase may be indirectly caused by the formation of more defined neighborhoods during initial link removal. As links connecting neighborhoods to each other are removed, there is increasing reliance on the one or two remaining links. The nodes adjacent to these links thus have higher betweenness measures and become more vital to the network, so much so that their betweenness outweighs that of the nodes losing adjacent links. Eventually, there are not enough links remaining to create neighborhoods and, at this point, the network betweenness quickly drops.

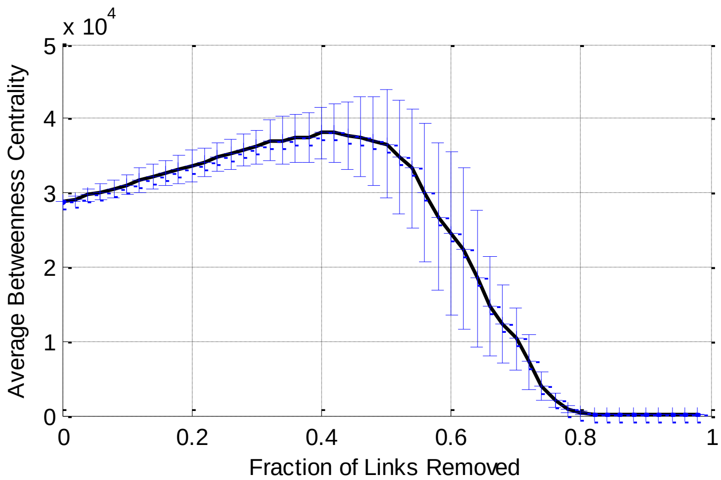

Figure 5. Effect of random link removal on average nodal betweenness centrality

The average shortest path of the network has arguably the strongest correlation to the redundancy of the system. When considering route options to travel from one destination to another, commuters often desire the shortest combination of roads. In topological graph theory, this is the shortest path from two network nodes, quantified by the number of links necessary to traverse from the origin to the destination. The average shortest path takes all possible combinations of nodes into account. Fig. 6 shows the effect of link failures on the value of the average shortest path in the network. There is a steady increase in this parameter until approximately 0.5 of links are removed, when the path length rapidly grows before converging at a maximum. When there is no possible path between two nodes, the length of the shortest path is infinitely large. For the purposes of containing the trend in a reasonable range of values, this infinite upper bound is set to 1000 and is visible as a maximum limit (Fig. 6). As soon as just one set of nodes has an infinite path, the average will jump. At this sudden change in slope, there is a sufficient number of links removed to force the shortest path towards infinity, representing complete disconnection across the network. Along this section of the plotted average, from about a 0.5 to a 0.8 link removal fraction, there were highly varied results with standard deviations significantly greater than those in the first portion of the curve. Despite the overall increasing trend towards a maximum path value, the response of the shortest path is clearly dependent on the location of nodes removed. This is an expected result of randomizing the link removal patterns. Certain simulated post-extreme event networks were able to hold connectivity for larger link removals. Others experienced sudden increases in the average shortest path length. The average trend, however, is problematic in the occurrence of an extreme event; transportation would be virtually impossible.

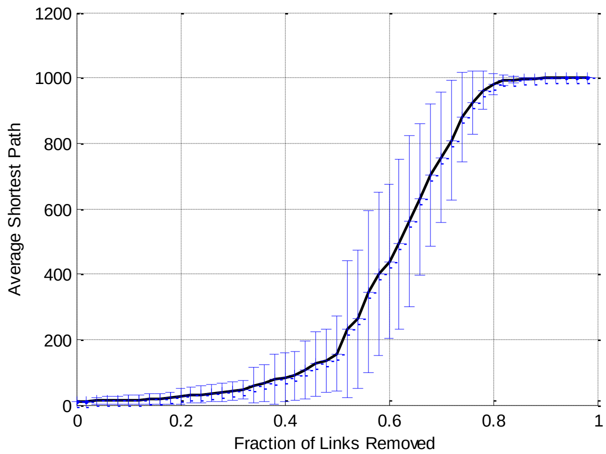

Figure 6. Effect of random link removal on average shortest path

RESULTS AND CONCLUSIONS

The robustness and resilience the San Francisco highway network is measured using the topological characteristics of the network. In all parameters measured, the removal of links forces the eventual deterioration of the functionality of the network. However, the unexpected initial positive effects on network betweenness and the clustering coefficient may hold important answers for methods to improve network response to an event. After improving and developing highway infrastructure to higher standards of resiliency, these curves can also be reanalyzed to evaluate effectiveness. By knowing the desired trend and values of a particular topological measure, efforts to redesign or rebuild parts of networks can be directed efficiently. There are a variety of methods to quantify the resilience of a system, but the results of this topological graph study proved significant in quantifying a network response.

Future studies would benefit from localized random link removal, better simulating the network failures resulting from a seismic event-perhaps one of the most probable extreme events to consider for the San Francisco highway system. This investigation simulated a random attack with arbitrary link removal across the entire network. Additionally, an even wider holistic approach to studying resilience may analyze more graph parameters and measures to study resilience from a variety of points.

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