Robustness of Transportation Networks under Megaregion Evacuations

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16. Abstract

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Disruptions in Megaregional Network Evacuations: Identifying and Assessing Critical Links

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Abstract

Mass evacuations are a protective action to move large populations from hazardous areas to safety. However, even the best-planned evacuations can be slowed by unexpected disruptions, such as traffic incidents. Even minor disruptions can significantly slow evacuations, so it is critical to understand which links are most vital to the operation of the system. This paper describes a study to address that need by developing a method to evaluate large networks more efficiently to identify links that disproportionately increase network delay when affected by disruptive incidents. The study is unique because it examined the impact of individual link disruptions over a megaregional network covering thousands of square miles while drastically reducing the computation time necessary for a traditional full-scan analysis. In the research, link criticality was quantified by an index using factors such as alternative path availability, global maximum flow properties, modified betweenness centrality, and hazard exposure. Links with high indices established an initial "most-critical" list, then agent-based simulation was used to quantify the network-wide effects of disrupting these most-critical links. Results showed that links with the highest indices often had the fewest alternative paths to avoid them. Thus, while incident effects tended to be localized, findings suggest that networks with more path alternatives tend to have higher overall resilience to disruptions. By giving the ability to reduce computational efforts to evaluate large-scale networks, this methodology can be used in emergency planning to focus monitoring on the most important areas and allow them to be monitored for disruptions to maintain network efficiency.

Keywords

sustainability and resilience, disaster response, recovery, and business continuity

The southern coastal region of the U.S.A. has a long history of impacts from natural disasters. The central Gulf Coast megaregion from New Orleans, Louisiana, to Houston, Texas, in particular, is at-risk because it provides support to the oil and gas industry, is crisscrossed by hundreds of waterways vital to national commerce, and encompasses more than 10 million people that live, work, and vacation within 50 mi of the coast. Throughout history, catastrophic events such as hurricanes have posed huge risks to property, infrastructure, and, most importantly, the lives of residents in susceptible areas. To lessen the risks of major storm events, mass evacuations are commonly used to move coastal populations to inland areas to shelter.

Planning and managing evacuations in densely populated areas of multiple interconnected, overlapping metropolitan centers can often become complicated as huge numbers of people are required to move during short time spans using complicated, overlapping routes. Evacuation processes are often further affected by disruptive incidents. Even routine small-scale incidents such as traffic crashes and mechanical breakdowns can limit the capacity of regional road networks. This study explores new methods to assess and evaluate ways to enhance the ability of megaregional highway traffic

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networks and permit them to better absorb and recover from evacuation-related disruptions.

While prior research has focused individually on the effects of traffic incidents (*1–4*) and emergency evacuations (*5*), few have focused on traffic incidents during evacuations (*6*) or evacuations of megaregions (*7*). Similarly, little to no prior research has been done to investigate the impact of disruptions on evacuations at the megaregion level. Assessment at this scale is growing in need and importance, especially for areas where separate cities are growing into continuously populated regions with overlapping road networks. Combined, these issues and trends have created the need for research to more effectively assess the effects of disruptive events on megaregion emergency evacuations.

A commonly used method for measuring network resiliency and the effect of disruptions on large-scale networks is through full-scan network analyses using traffic simulation. However, the large size and complexity of megaregional transportation networks make the use of traditional simulation methods complex and very time consuming, if not completely infeasible. With that need in mind, this research introduces a new performance index to describe the importance of each road segment in a megaregion network under evacuation conditions. The index accounts for several factors, both local and network-wide. Among most notable were local effects of road segment closures and network-wide effects of any specific link closure on aggregate flow and clearance time, as well as other topological and geometric characteristics of the network.

By converting each of these factors into a single composite index, every link in a megaregion-sized network can be ranked by criticality in a matter of minutes. Then the ranked link indices can be used to narrow down the search for the most-critical links in the network from the standpoint of disruption-criticality. After identifying the most-critical links, a simulation can be run for the top candidates from the list. This approach allows us to focus on a much smaller set of links (e.g., the top 50) rather than on all the links in the megaregion network, which could number in the tens of thousands. The effects of each link's removal can be examined and analyzed individually via simulation by using appropriate performance measures. This study applies this methodological framework and tests its effectiveness to answer the question of how to identify the most-critical links in large-scale transportation networks considering traffic incidents during an emergency evacuation. Ultimately, the results of the analyses can be used to develop priority roads for improvement and monitoring to increase network resilience.

The research effort is summarized in the following five sections of this study. In the literature review that follows, findings and prior studies related to link criticality, traffic incidents, emergency evacuations, infrastructure resilience, and megaregions are discussed. Next, the study objectives and the proposed methodology are described, including the introduction of the novel network performance index and case study data collection. This is followed by the computational modeling results and cross-comparisons of the data categories in the study. Finally, the paper closes with a brief summary of overarching results, a description of the contributions of this research to the body of knowledge, and avenues for future research.

Literature Review

A literature review was conducted on the topic of disruptive events in transportation networks during both normal and evacuation scenarios, as well as link criticality and vulnerability. While many studies have been done that describe the effects of traffic disruptions on network performance, only a few have focused on disruptions during evacuation scenarios or in megaregional areas. These topics were explored to understand how each uniquely contributes to the current study of transportation network disruptions.

Critical link analysis is a multifaceted area of study that is related to several established study topics, such as vulnerability, resilience, and robustness. Several studies in the literature present methodologies to identify critical links in a network while avoiding prohibitive computational burdens. Sullivan et al. (*1*) propose a performance measure called network trip robustness (NTR) to accomplish this. It is more directly based on the traditional network robustness index (NRI), which measures the network-wide effects of link removal using a traditional full-scan method. The NRI aggregates the product of traffic flow and travel time for each link across the network in the case where no links have been removed and compares it to the case where a link has been removed. The difference in these values reflects the degree to which a link's removal has negatively affected the overall network performance. Sullivan et al. developed the NTR by summing the NRI values across the network and dividing by the total demand between all origins and destinations in the network. The NTR also considers multiple levels of capacity disruption in its analysis, not only complete removal from the network. For very large networks, however, the time and computational resources needed for the full-scan technique are infeasible in magnitude.

A 2020 study by Li et al. (*4*) similarly aims to reduce prohibitive computation times with the use of a NRI-based performance index called the traffic flow betweenness index (TFBI). This index is similarly based on values such as traffic flow, demand, and number of shortest paths, which attempt to capture both the static and dynamic characteristics of the flow through the network. A list of candidate links is first created to reduce the number of iterations necessary for the criticality analysis. However, Li et al.'s method does require the direct use of NRI values to weight the terms of the TFBI equation presented, and since obtaining NRI values requires the traditional full-scan simulation method, the excessive computation times cannot be avoided with this technique.

Several papers implement a grid-based technique to investigate the network-wide impacts of traffic function losses while reducing the computational burden demanded (*8–10*). This technique involves dividing the study area map into a grid of identical rectangular areas, each of which are removed from the network iteratively. These studies use the idea that when natural disasters such as flooding or wildfires occur, multiple network elements near to one another are usually affected or closed rather than single links or nodes. Since this method groups multiple adjacent links together and removes them simultaneously, less computation time is needed to evaluate the entire network as opposed to testing each individual link. Although these studies aim to reduce computation times by limiting the number of simulation iterations needed, much like this current study does, it does so by a very different method. Instead of grouping links by proximity for simultaneous removal, the current study uses a performance index that can be calculated for each link before the simulation phase to focus the efforts of simulation on a small group of candidates for the most-critical links in the network.

Jung et al. (*8*) also employ the use of centrality measures in the grid methodology. The betweenness centralities (BCs) of all the grid cells are measured before and after the removal of each cell, and the influence of each cell's removal on network flow can be measured by the sum of the variations in the BCs of the other cells. The study also emphasizes the differences between the local and global effects of different network attack strategies. It was found that attacks based on link degree (or node degree) are very disruptive to the immediate area (local effects), while attacks based on facility betweenness are most harmful to the network as a whole (global effects).

Wildfire evacuations in remote areas are the focus of two studies reviewed. Mahajan and Kim (*9*) analyze the transportation network of northeast Alberta to examine vulnerabilities during wildfires based on betweenness, accessibility, and facility characteristics. A distinction is made between network vulnerability and community vulnerability. While network vulnerability describes restrictions in the available transportation capacity, community vulnerability focuses on the accessibility of emergency services and service centers during a natural disaster event. While this study does explore network vulnerabilities during an emergency evacuation, the focus is mainly on identifying critical communities and supporting intermodal infrastructures, which is beyond the scope of this current study.

Ohi and Kim (*10*) also use a grid-based method to analyze a transportation network with reduced computation time. Similar to this current study, Ohi and Kim utilize the min-cut max-flow theorem to explore the contributions of individual links to the network bottleneck capacity during wildfire evacuations. Their results show that the areas that contribute the most to network bottleneck restrictions during evacuations are always found adjacent to the evacuation communities. This information could be very useful for emergency planners preparing for wildfires and other natural disaster scenarios.

Chen et al. (*2*) seek to identify critical links while reducing the full-scan computation time but utilize a different approach. Based on the assumption that traffic incidents frequently only impact the immediately surrounding areas, the entire network does not need to be analyzed every time a link is removed. Instead, Chen et al. pre-select an "impact area" for analysis with each link's removal, thus significantly reducing the computation time needed. However, this approach only accounts for the local effects of disruptions and ignores the global impacts of disruptions. Other studies take the opposite approach and focus on the global impacts of disruptions while ignoring the local impacts. Xu et al. (*11*) use a global optimization method to analyze the network-wide effects of link removals and ignore the local effects. While this does reduce the computational burden, it does not account for the full range of impacts that occur.

Murray-Tuite and Mahmassani (*12*) actively seek to account for both the local and global effects of traffic disruptions in their 2004 study. The study accounts for travel time, capacity, and availability of alternate paths in a game theory approach to calculate two indices: a vulnerability index for the local impacts and a disruption index for the aggregate global impacts.

Knoop et al. (*13*) examine vulnerability at multiple levels of disruption; however, the study focuses on smaller, urban networks. Knoop et al. explore combining existing indicators to measure vulnerability but conclude that these indicators fail to reliably determine link vulnerability. Studies such as those of Jenelius (*14*) and Ukkusuri and Yushimito (*15*) focus their vulnerability and criticality analysis methods on large networks, and Jenelius also includes exposure in the analysis. Ukkusuri and Yushimito explore the use of the volume-to-capacity ratio (V/C), a commonly used metric that describes a link's traffic volume as a fraction of its total capacity.

The study shows that, even though the V/C value is useful, it is not enough to measure criticality on its own.

Another powerful method for analyzing transportation networks is computer simulation. Traffic simulation software is a commonly used tool for evaluating the effects of network disruptions. Several studies utilize traffic simulation techniques to explore emergency evacuation scenarios during natural disasters (*16–18*). These simulations can be used to examine a variety of issues related to evacuations: link disruption effects, effectiveness of proposed traffic control strategies, and other network performance measures. Simulation technology has developed significantly over the past two decades and continues to provide innovative methods for evaluating complex transportation networks, especially those that cover wide geographical areas with many users.

Both Chiu et al. (*16*) and Zhao and Wong (*17*) simulate evacuation traffic flows to test the effectiveness of traffic control measures such as contra-flow and phased evacuations. While this current study utilizes a microscopic simulation to track the movements of individual vehicles, Chiu et al. use a mesoscopic simulation program (Dynamic Urban Systems in Transportation [DynusT]), which incorporates elements of both microscopic and macroscopic simulations to analyze traffic scenarios in large-scale regional areas, especially vulnerable coastal communities. Although the study focuses on the effectiveness of strategies such as contra-flow and phased evacuations, Chiu et al. emphasize why it is important to study disruptions during emergency evacuation like this current study does: when a network is already operating near or at full capacity, as they are during evacuations, simple incidents like a stalled vehicle can cause far-reaching cascading congestion problems throughout the network. Minimizing the effects of such disruptions is important for transportation researchers and emergency managers.

Zhao and Wong (*17*) conducted a similar study more recently that explores evacuation strategies such as contra-flow and phased evacuations for wildfire scenarios in Berkeley, California. A spatial-queue-based dynamic traffic simulation uses Global Positioning System (GPS) rerouting data to reduce vehicle exposure and clearance times during evacuations. The study focuses on attempting to minimize the number of evacuating vehicles while creating effective communication and parking plans. It was found that phased evacuations can help to reduce vehicle exposure, but clearance times might increase. Contra-flow was shown to reduce both vehicle exposure and clearance times when paired with fire-slowing strategies.

Traffic simulation has also been used to model hurricane evacuations. Edara et al. (*18*) model the evacuation of large-scale transportation networks under different hurricane strength conditions in their 2010 study. While this current study only considers one hurricane approach scenario, Edara et al. explore the effects of different storm severities on traffic performance measures, bottleneck locations, congestion propagation, clearance times, and other operational difficulties. The microscopic simulation was developed using VISSIM software, and parallel processing methods are suggested to reduce long computation times. The study accomplishes this by breaking up the main network into subnetworks, which are analyzed on parallel processors and re-combined later. The findings show that large networks have different simulation needs than small networks.

In addition, the use of GPS data by drivers for routing purposes has increased dramatically over the last two decades. This and even more advanced types of real-time traffic information delivery can have a significant impact on driver route choice during incidents. Khoo and Asitha (*19*) note the importance of this in their 2016 study, while also pointing out the limitations of GPS data usefulness. Sometimes the GPS signal is not able to be received by the driver, and other types of data can offer more real-time information than static GPS devices.

Significant attention has been paid in the literature to the individual topics of critical link identification, emergency evacuation traffic flow, and megaregion traffic flow. However, no studies have proposed a method to identify the most-critical links of a megaregional transportation network during an emergency evacuation. This study aims to fill that gap by presenting a methodology to create a list of critical link candidates from across a large network during an evacuation scenario that can be utilized in a traffic simulation program without requiring excessive computation times. The proposed performance metric accounts for variations in link failure probability and considers both the local and global effects of a link's removal. This methodology will be described in detail in the following section.

Methodology

Because of a lack of consensus in the scientific community on how to best quantify traffic network resilience, especially in large networks and during emergency scenarios, this paper seeks to identify the most-critical links in a megaregion network during an evacuation using a new performance index. This index is composed of multiple terms that have either been newly developed or adapted from commonly used measures. This index can be used to analyze properties of networks without needing the temporal and computational burden of simulating a full-scan analysis.

Consider a directed network represented by a graph $G = (N, L)$ such that N is the set of all network nodes, containing n_N number of nodes, and L is the set of all links, containing n_L number of links. Each link l_i is labeled such that $i = 1, 2, 3, \cdots, n_L$, and each node n_j is labeled such that $j = 1, 2, 3, \cdots, n_N$. An asterisk will be used to mark a link that has been removed from the network (l_i^*). We denote the set of origin–destination (O/D) pairs with W containing n_W.elements, and we will let Π represent the set of paths between each O/D pair w, containing n_Π paths, each denoted by π. Similarly, P^* will represent the set of all unique paths that can be used as alternates to link l_i^* on its removal from the network. This set contains n_P paths, and each path p_r is labeled such that $r = 1, 2, 3, \cdots, n_P$.

The demand on the network D is estimated for all $w \in W$. We will denote traffic flow over link l_i with V_{l_i} and a link's capacity by C_{l_i}. Here, v_{l_i} and c_{l_i} are used to refer to flow volume and capacity at the bottleneck location of each unique alternative path p_r to link l_i. We define the bottleneck location as the link along each alternative path with the highest V_{l_i}/C_{l_i} ratio. Volume–capacity ratios are commonly used to measure congestion on traffic links, and these values will determine which link on each alternative path is the most sensitive to increased flow because of diversion from the closed link l_i^*. User travel cost for link l_i is represented by K_{l_i}, and total user travel cost for alternate paths uses the lowercase $k_{l_i}^{p_r}$, while free flow travel time is denoted by $t_{l_i}^0$. Where applicable, values measured before a link's removal are marked by a superscript b, and those calculated after a link's removal are written with a superscript a. Flow volumes are determined using the user equilibrium model, and the travel costs are based on travel times computed using the Bureau of Public Roads function.

Performance Index and Term Definitions

Once the network demand has been loaded and the link travel costs have been calculated, the criticality of each link found in a shortest path can be examined by the implementation of the proposed index. The index is a combination of novel concepts and modifications to existing measures. This index analyzes the criticality of specific links in the network by showing which link's removal causes the greatest damage to network performance. Each term seeks to approach the problem from a unique perspective to account for all facets of the network effects of the link disruption. Links that are more critical will have a greater index value, while links that are less critical will return a smaller index value. The equation is as follows:

$$Index_{l_i} = \left(AP_{l_i}^{norm} + MF_{l_i}^{norm} + BC_{l_i}^{norm}\right) * \left(\lambda_{l_i}^{norm}\right) \quad (1)$$

where AP_{l_i} is the alternative path term for link l_i, MF_{l_i} is the maximum flow term for link l_i, BC_{l_i} is the BC of link l_i, and λ_{l_i} is the exposure factor for link l_i. Each of these terms is normalized before being used in the equation. The following sections introduce each term in detail.

Alternative Path Term. When a driver encounters a disrupted link along their route during an evacuation, an alternate path must be found if they wish to reach their destination. The number, capacity, and topology of these potential paths can have a dramatic impact on the increase in travel cost a driver will face because of rerouting. Depending on the magnitude of the traffic volume being displaced and the capacities of the disrupted link and its alternative paths, the driver may experience a large inconvenience with high travel costs, a small inconvenience that is only slightly more costly than their original path, or an inability to reach their destination (in the case of an isolating link being disrupted). As Chen et al. (*2*) note, there is empirical evidence that a link failure has significant impacts mainly on the nearby links and nodes. Therefore, the proposed alternative path term accounts for these local effects.

This study defines an alternative path term that describes the criticality of link l_i not only by the number and availability of viable alternative paths, but also by the ability of those alternative paths to efficiently accommodate and reroute the flow of link l_i after its removal from the network. This was achieved by considering link l_i and its alternative paths as an isolated system between two adjacent nodes. The bottleneck locations on each unique alternative path p_r are found by selecting the link from each path with the highest V/C. When the diverted traffic flow from link l_i^* is added to the alternate paths, these are the locations that will limit the performance of the whole path the most. Then cumulative V/Cs are calculated for the mini-system before and after the removal of link l_i^* and the difference between the two is measured. This value is then related to the modified count of unique alternative paths available, n_p^*. This is shown in detail via the following equation:

$$AP_{l_i} = \left(\frac{V_{l_i} + \sum_{p=1}^{n_p} \Omega\left(k_{l_i}^p\right) v_{l_i}^p}{\delta_{l_i} C_{l_i} + \sum_{p=1}^{n_p} \Omega\left(k_{l_i}^p\right) c_{l_i}^p} - \frac{V_{l_i} + \sum_{p=1}^{n_p} \Omega\left(k_{l_i}^p\right) v_{l_i}^p}{C_{l_i} + \sum_{p=1}^{n_p} \Omega\left(k_{l_i}^p\right) c_{l_i}^p} + \delta_{l_i} \right) * \frac{1}{n_p^*} \quad \forall p \in P^* \quad (2)$$

where V_{l_i} is the flow volume of the disrupted link before disruption, $v_{l_i}^p$ is the pre-disruption flow volume of each alternate path (at its bottleneck location), C_{l_i} is the flow capacity of the disrupted link before disruption (assuming its capacity is zero after disruption), $c_{l_i}^p$ is the flow capacity of each alternate path at its bottleneck location (which will remain unaffected by disruption), $\Omega\left(k_{l_i}^p\right)$ is the probability of drivers choosing one alternative path or another based on their relative travel costs, n_p^* is the weighted number of alternative paths available based on their travel costs' relation to the disrupted link's original travel cost, and δ_{l_i} is equal to 0 if link l_i^* is a non-isolating link or is equal to 1 if link l_i^* is an isolating link.

The term $\Omega(p)$ was included to represent the probability of a driver choosing an alternative path based on its estimated travel costs, $k_{l_i}^p$. When link l_i^* is disrupted and removed from the network, its flow volume must be redistributed among the alternate paths. If one alternative path is more costly than another, fewer drivers will choose it; if both alternate paths have similar travel costs, the volume will be divided more evenly between the two. To quantify this mathematically, the following multinomial logit model was utilized:

$$\Omega(p) = \frac{e^{-\alpha k_{l_i}^p}}{\sum_{p=1}^{n_p} e^{-\alpha k_{l_i}^p}} \qquad \forall\, p \in P^* \qquad (3)$$

where k_i^p is the travel cost of an alternative path and α is a constant that must be calibrated for each network.

The term n_p^* similarly uses a travel cost-weighted calculation to obtain a numerical representation of how many alternative paths exist in each set of circumstances. Travel cost $k_{l_i}^p$ is expressed with respect to travel time, which is used to distinguish alternative routes with different attractions to drivers. In general, drivers may find a route with shorter travel time more attractive. The magnitude of the difference between the travel costs of the original disrupted link and that of the alternative paths was also considered. These factors are expressed by the following equation:

$$n_p^* = 1 + \frac{K_{l_i}}{\sum_{p=1}^{n_p} k_{l_i}^p} \qquad \forall\, p \in P^* \qquad (4)$$

where K_i is the travel cost of link l_i and k_i^p is the travel cost of each path alternative to l_i.

Maximum Flow Term. While the alternative path term considers the local effects of link closures, the maximum flow term seeks to describe the global effects of link removal. Calculating the maximum number of cars that can travel across a network from an origin to a destination during a given time period is an important network characteristic, especially during evacuations. Knowing where bottlenecks occur and how much they limit flow can help planners and administrators make important decisions with respect to emergency preparedness and infrastructure investment. This paper introduces a maximum flow term that seeks to quantify the effect of a link's removal on the maximum flow of traffic possible across the network from an origin node to a destination node. Abdullah and Hua (*20*) identify weak spots in transportation networks by using this method. The study uses the max-flow min-cut analysis as its only metric, while the current study seeks to incorporate this bottleneck information into a more comprehensive criticality analysis that also includes local impacts, BC, and exposure.

Because bottlenecks are areas of relatively low performance, this method seeks to find the disconnecting set with the lowest cumulative flow capacity. A disconnecting set refers to a set of links that if severed divide a network into two separate pieces. These locations denote the network bottleneck, and therefore this value equals the maximum flow possible through the whole network for the O/D pair.

This term calculates the maximum flow values of each O/D pair before and after a link's removal to determine its impact. A large difference in values from before to after link removal indicates a higher level of criticality. Summing these values aggregates the negative impacts of a link's removal across all O/D pairs. This process is represented by the following equation:

$$MF_{l_i} = \sum_{\pi\in\Pi}^{n_\pi} \left(\frac{\Phi_{l_i}^b - \Phi_{l_i}^a}{\Phi_{l_i}^b} \right) \qquad \forall\, w \in W \qquad (5)$$

where $\Phi_{l_i}^b$ is the maximum flow for O/D pair w before the removal of link l_i and $\Phi_{l_i}^a$ is the maximum flow for OD pair w after removal of link l_i^*. In this way, the global effect of a link closure on the network can be seen as the aggregation of all flow damages incurred through a link's removal from the network. This term is highly influenced by the demand loading on the network and could give crucial information about traffic flow during an emergency evacuation scenario.

Betweenness Centrality Term. To account for the topological characteristics of the network, a term based on BC was employed. BC describes the ratio of the shortest paths passing through a link (or node) to all the shortest paths in the network. This is a very useful topological concept that has become very useful to transportation engineers for analyzing network properties. Gauthier et al. (*3*) point out, however, that such static topological indicators do not account for the dynamic effects of traffic flow. Therefore, Gauthier et al. introduce a performance index based not only on BC but also on dynamic travel cost values. However, Gauthier et al. utilize a range of varying disruption levels, similar to Sullivan et al. (*1*). Takhtfiroozeh et al. (*21*) expand on this methodology and test several modified BC measures. The study shows that there are multiple ways to weight BC to give

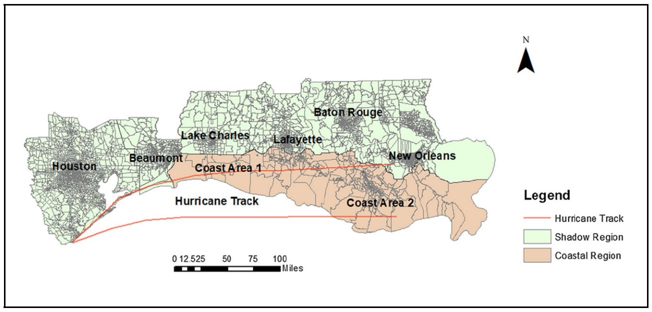

Figure 1. Map of the megaregion network and hurricane track.

more accurate criticality assessments. While the current study also utilizes a modified BC component, the proposed performance index has additional terms to account for other network factors, such as bottlenecks and alternative route availability.

Since the alternative path and maximum flow terms consider the dynamic characteristics of traffic flow, including a more topological term is appropriate. The equation for the BC term is as follows:

$$BC_{l_i} = \frac{\sum_{\pi \in \Pi}^{n_w} \mu_\pi}{n_w} \qquad \forall\, w \in W \tag{6}$$

where n_w is the estimated number of O/D pairs and μ_π equals 1 if link l_i lies on the shortest path π and equals 0 if it does not. Therefore, this term represents the ratio of the number of shortest paths in the network that traverse link l_i to the total number of O/D pairs in the network. This is an important measure for finding the topological importance of a link in a transportation system.

Exposure Factor (λ). The exposure term describes the probability that an incident will occur on the link in consideration. Although the Highway Safety Manual provides accident rates for different road types, other methods are necessary to reflect the unique conditions found during an evacuation, such as higher accelerations and elevated crash risks (*6*). Because of the unique properties inherent to traffic flow patterns during evacuations, a different method for determining the probability of a link failing is needed. An exposure term is proposed based on link length and traffic flow. Jenelius (*14*) demonstrates that length can be used as an indicator of disruption probability, and Hasan and Rahman (*6*) show how flow rates and crash rates followed similar trajectories during evacuations. The calculation of the exposure factor is as follows:

$$\lambda_{l_i} = \left(\frac{x_{l_i}}{\bar{x}}\right)\left(\frac{V_{l_i}}{V_{total}}\right) m_{l_i} \qquad \forall\, l_i \in L \tag{7}$$

where λ_{l_i} is the exposure factor, x_{l_i} is the length of link l_i, $\bar{x}$ is the average length of all links in the network, V_{l_i} is the flow volume across link l_i, V_{total} is the total flow in the network, and m_{l_i} is the number of lanes traveling in the direction of flow. In this way longer links carrying a greater amount of traffic will be considered more critical than shorter, less-used links. These values are then normalized and multiplied to the sum of the first three terms to determine the list of most-critical links in the network.

When this index is applied to a transportation network model, the links with the highest index values comprise the list of top candidates for the network's most-critical links. The simulation can then be run for the iterative removal of any desired number of links. The outputs of the simulation (travel times and queue lengths) are analyzed to ascertain the effects of these link removals on network performance during an evacuation scenario. This process is applied to a model of the Gulf Coast megaregional network in the following section, accompanied by an analysis of the data collected.

Case Study Description

Emergency evacuations are considered major transportation events and have been widely studied in the literature. Hasan and Rahman (*6*) acknowledge the uniqueness of evacuation scenarios analyzing evacuation crash data. Zhang et al. (*22*) explore network clearance times in evacuations on a macroscopic scale without considering microscopic factors. Overall, past studies are more conceptual and operational in nature without examining the specifics of traffic flow.

The proposed index was applied to the transportation network of the U.S. Gulf Coast megaregion as a test bed to demonstrate how the index performs in determining the network impacts of link removal during an evacuation. The network analyzed in this study covers the megaregion from Houston, Texas, to New Orleans, Louisiana, including the metropolitan areas of Baton Rouge, Lafayette, and Lake Charles, Louisiana, as well as Beaumont, Texas. The network, seen in Figure 1, was developed using ArcMap 10 GIS software by Zhang et al. (*23*). The figure also shows the projected hurricane track causing the evacuation, determining the simulation demand loading.

The megaregion traffic model was developed in TRANSIMS (an agent-based microscopic traffic simulation) using 2010 census data. The modeled "base case" event was a single day evacuation from an unnamed Category 4 hurricane that threatened the Gulf Coast. A multinomial logit destination choice model, developed by Cheng et al. (*24*), was applied to forecast the destination choice for over one million evacuating vehicles. The model produced the probability of each destination being selected based on several destination characteristics, such as distance from origin, hazard level, population, and

Table 1. Performance Index Results of the Top 10 Candidate; Links (From Equation 1)

Index rank	Link number	Road type	Number of lanes	Capacity (vph)	Length (mile)	Index value	Normalized index value
1	55,290	Local	2	1600	11.1	0.21	1.00
2	16,977	Major	2	1600	37.5	0.19	0.88
3	55,299	Local	2	1600	2.9	0.14	0.66
4	54,965	Freeway	2	2500	16.5	0.10	0.51
5	5599	Freeway	2	2500	8.8	0.08	0.38
6	7499	Freeway	2	2500	15.5	0.07	0.33
7	55,296	Freeway	2	2500	19.4	0.07	0.31
8	54,967	Freeway	2	2500	5.4	0.07	0.31
9	55,304	Freeway	2	2500	19.4	0.07	0.31
10	16,404	Freeway	2	2500	10.1	0.07	0.31

Note: vph = vehicles per hour.

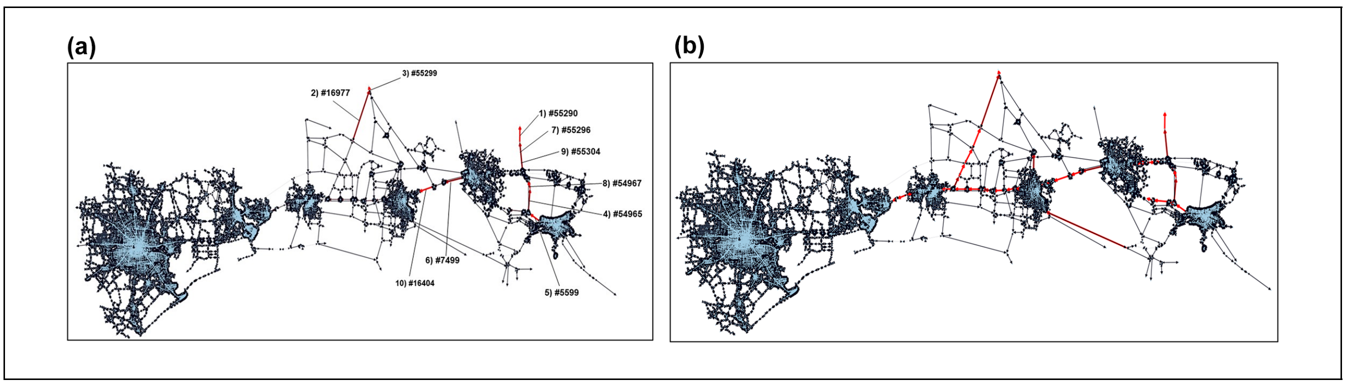

Figure 2. Map of the megaregion network showing the location of top critical link candidates: (*a*) top 10 critical link candidates and (*b*) top 50 critical link candidates.

racial makeup. Evacuees were assumed to use auto-based self-evacuation as their mode of travel. A time-dependent sequential logit model (TDSLM) developed by Fu et al. (*25*) was applied to forecast the evacuation departure times. This is achieved by representing departure timing decisions as "a series of sequential binary choices over discrete time periods" until a decision is made (*23*). TRANSIMS also contains internal algorithms for modeling traffic control. For more details with respect to the development of the TRANSIMS model, readers are referred to Zhang et al. (*23*). Next, to assess the effect of link removal on the traffic network during an evacuation, the links with the highest index values are the top candidates for the most-critical links in the system and are iteratively removed in the model. The next section presents the simulation outputs and results analysis.

Results

Once the performance index has been defined, it can be applied to each link along all possible paths in a large-scale network. The higher the value associated with a link, the more critical it is to the network's performance. For an evacuation scenario, the performance index seeks to narrow down the choices of most-critical links to a short list of candidates for removal in the simulation. Once the candidate list is obtained, each link is iteratively removed from the network, and the impact of the removal is assessed through a variety of performance measures. The impact can be seen by comparing these measures to the base case scenario in which no links are removed from the network.

Developing List of Critical Link Candidates

After applying the index, the links were ranked according to the calculated values. These links are shown in Table 1 and highlighted on the map in Figure 2, with Figure 2*a* showing the locations of the top 10 candidate links, and with Figure 2*b* showing the locations of the top 50 candidate links across the network. These links lie largely along the main interstate corridors and major highways heading both east–west and north–south, many of which coincide with segments designated by the Louisiana Department of Transportation and Development (DOTD) as official hurricane evacuation routes. This is to be expected for a few reasons. Interstate highways usually carry high traffic volumes, especially during evacuations, with very few or no alternate routes available. Particularly on the area's many bridges, a disturbance could leave travelers stranded with no alternative routes to their destination. This situation would likely return a high index value. Because of the importance of exposure to disruptions, longer links rank higher. In addition, the eastward approach of the modeled hurricane caused much more traffic movement in the eastern portion of the megaregion. This can explain why the top candidates are found mostly in Louisiana and not Texas. Inland movement is a basic protective maneuver during hurricane evacuations, which explains why evacuation routes running perpendicular to the coastline are found to be critical. Segments of Interstate 55 North and US-165N are some of the most critical to network performance.

It is important to note the locations of these links with the highest performance index values. Intuitively, one would expect that freeways would be relatively critical to any large movement of vehicles, and indeed seven out of the top 10 most-critical candidate links were found along freeways. Since freeways carry larger volumes of vehicles at higher speeds with fewer options for rerouting, it is understandable that their performance index values would be high. The highest listed freeway links are those that have very limited options for alternate routes because they are long bridges over open water, including the Manchac Swamp bridge (#4) and the Bonnet Carré Spillway bridge (#5). The findings of Li et al.'s (*4*) study support the simulation findings from this current study. Their microsimulation shows that the facilities ranked with the highest criticality were those that carried high volumes of traffic with few or no alternative routes available. The top three links in Table 1 are local and major northbound links on the northern edges of the network. These links are important for moving people away from the hazardous coastal areas, and since there are a limited number of routes leading vehicles out of the network to the north, it is understandable that these links would be burdened with carrying the majority of vehicles seeking to leave the modeled area to the north, amplifying their importance and criticality.

Traffic Simulation

To verify the findings of our performance index, each of the top 50 candidate links was iteratively removed from the network, and the traffic simulation was run. While other studies use traffic simulation to model evacuation processes, they tend to focus on other variables, such as hurricane strength, traffic control strategies such as phased evacuations, and minimizing the number of evacuating vehicles. The simulation utilized here focuses on one hurricane scenario with a non-phased evacuation plan and a constant number of evacuating vehicles. Performance measures such as vehicle hours of travel, vehicle hours of delay, average queued vehicles, and maximum queued vehicles are generated by the simulation software as output. These outputs are then analyzed. The results represent an average of 20 individual model iterations, and depending on the processing units available, each scenario run can take up to one day at most. A significant contribution of this study is the reduction of the computation time by testing a predetermined number of most-critical links from the developed list instead of testing every link in the network. Because of the duration of each individual simulation run, it would require prohibitively long computation times to perform this task if every link in the network were analyzed, even if using multiple computing devices. Procuring the list of top candidates turns this infeasible challenge into a manageable task to be completed within a few days.

These four performance measures are produced first for a base case scenario where the full network is considered with no link removals. Then the top critical link candidate is removed from the network, and the performance measures are generated and collected for this scenario. This process is repeated iteratively, each time removing the next most-critical link from the candidate list, while replacing the previously removed link so that only one link is removed from the network for each simulation. This data can be seen in Table 2. The removal of each link causes an increase in the hours of vehicle travel and delay, as well as an increase in the number of queued vehicles. Links higher on the candidate list cause larger increases in these measures, with a general downward trend as we move down the candidate list. This trend provides positive reassurance of the performance index's usefulness.

The percentage change in the values compared to the base case for each of these performance measures for the top 50 candidate links are represented graphically in Figure 3, *a–d*. In each graph the top 10 candidate links consistently show the most pronounced increases in travel delays and queues on removal. For example, Figure 3*a* shows that each of the top 10 candidate links causes an average of at least 12% increase in travel delays, with nearly half of those causing 30%–40% increases. On removal of these same links, average queue lengths in the network increased from 25% to over 60% according to the simulation outputs. The consistency in these findings offers support to the validity of the candidate list developed using the performance index.

The simulation results generally indicate that the removal of critical links causes a significant increase in travel time. This supports the findings of previous studies, such as Alam and Habib (*26*), which show that

Table 2. Performance Measures of the Base Case and Top 10 Candidate Link Removals from Simulation

Index rank	Link number	Road type	Vehicle hours of travel	Vehicle hours of delay	Avg. queued vehicles	Max. queued vehicles
(Base case)	na	na	716,122	169,950	85,130	181,920
1	55,290	Local	759,359	225,486	133,579	234,176
2	16,977	Major	754,737	220,149	130,875	231,891
3	55,299	Local	749,730	213,015	128,986	229,929
4	54,965	Freeway	769,610	232,284	137,481	252,005
5	5599	Freeway	746,052	212,005	125,094	221,014
6	7499	Freeway	745,642	208,987	119,987	219,045
7	55,296	Freeway	740,923	204,765	113,988	218,438
8	54,967	Freeway	768,322	230,538	135,114	248,352
9	55,304	Freeway	771,092	238,866	127,473	244,023
10	16,404	Freeway	733,978	190,983	106,972	212,939

Note: Avg. = average; Max. = maximum; na = not applicable.

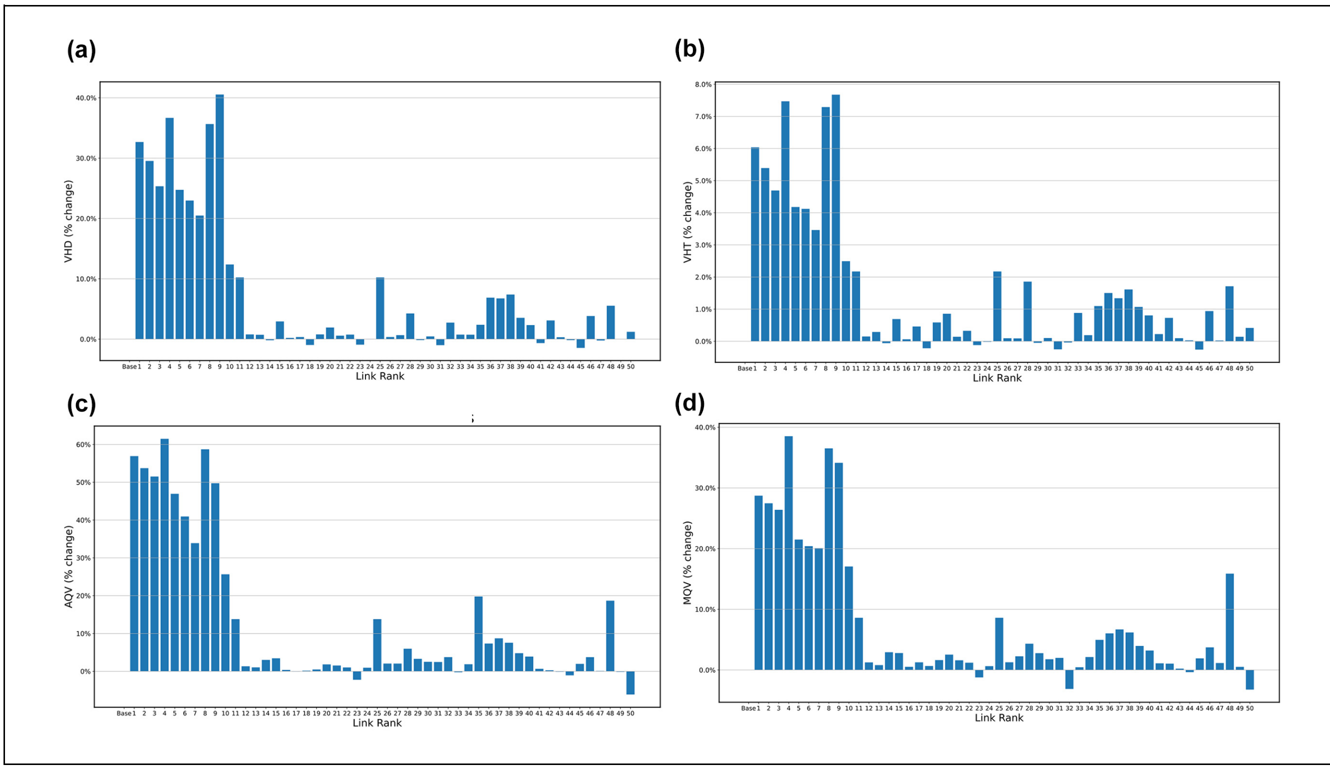

Figure 3. Performance measures of the top 50 critical link candidates (*a*) by vehicle hours of delay (VHD), (*b*) by vehicle hours of travel (VHT), (*c*) by average queued vehicles (AQV), and (*d*) by maximum queued vehicles (MQV).

disruptions during mass evacuations can have major impacts on facets of traffic flow and mobility, such as extended delay times and longer queue lengths.

An interesting finding among the simulation performance metrics is a handful of links whose removal appears to cause a reduction in both travel delays and queue lengths. These instances are marked in Figure 3, *a*–*d*, by those links whose bar extends downwards below the 0.0% mark on the *y*-axis instead of upwards. For example, the link ranked 23rd by the performance index consistently produces negative values in each of the four simulation performance measures. While this may seem surprising, this phenomenon has been observed before in the literature. It is called "Braess' paradox," and it states that sometimes adding a link to a transportation network can cause an increase in delays across the network. This also therefore implies that network performance can be improved by the removal of certain links, which forces

Table 3. Comparison of the Top 10 Candidate Link Rankings from Calculated Index Values and Simulation Performance Measures

Link number	Road type	Index rank	Normalized index value	Simulation rank	Avg. percentage performance change
55,290	Local	1	1.00	4	32.40
16,977	Major	2	0.88	5	32.21
55,299	Local	3	0.66	6	28.45
54,965	Freeway	4	0.51	1	28.24
5599	Freeway	5	0.38	7	24.86
7499	Freeway	6	0.33	8	23.31
55,296	Freeway	7	0.31	9	20.91
54,967	Freeway	8	0.31	2	18.53
55,304	Freeway	9	0.31	3	15.38
16,404	Freeway	10	0.31	10	12.41

Note: Avg. = average.

vehicles off links that easily become congested but may otherwise seem desirable. Sullivan et al. (*1*) encounter this situation when evaluating network performance while partially degrading the functionality of individual links in a network. The network shows decreased performance when a link is partially closed, but improved performance when the link is fully closed. These findings suggest that it might be in the best interests of traffic operators to advise drivers to avoid certain routes during an evacuation scenario to improve overall flow through the network.

The simulation output data collected for the top 50 candidate links are further analyzed to show which links cause the overall largest change in the simulation performance measures observed by TRANSIMS in comparison to the base case. This is achieved by averaging the percentage change in each of the performance measures for each link and sorting the list from the largest change to the smallest. This data is reflected in Table 3. The first set of columns shows the previously established ranked list of top 10 links using the previously introduced performance index, while the second set shows these links' new rankings based on the average change in the simulation performance measures. Note that the set of links contained in the top 10 ranks of each list are identical, but in a slightly different order. For example, link 54,965 ranks as the fourth most-critical link according to its calculated index value. This same link, however, produces the highest average percentage change in simulation performance measures, as denoted by the first place rank in the "Simulation rank" column. The top-ranked links for average travel time in Figure 3*a* (links ranked 1, 4, 8, and 9 by the index) are all found atop the newly ranked list. Also, the Spearman rank correlation between the set of top 50 links with respect to index values and the set of top 50 links with respect to simulation performance measures shows a good correlation with $\rho = 0.643$. Highlighting the similarities between these two lists helps to affirm the usefulness and accuracy of the proposed performance index.

Conclusion

The goal of the research described in this study is to improve mass evacuation transportation planning in large-scale networks. As coastal population growth continues to outpace the capacity of its road networks, there is a growing need for methods of identifying and addressing evacuation problem areas. One of challenges is identifying vulnerable areas in large and complex networks. Even more critical is identifying specific sections of road that could have broader, cascading effects on other routes in the network when disrupted. As Chiu et al. (*16*) point out in their 2008 study, when networks are heavily loaded like they are during an evacuation event, even small disturbances to the network can have drastic and far-reaching negative effects.

The contributions of this work are two-fold. The first is the development of a performance index that can be applied to determine individual link criticality based on both the local and global effects that its disruption could create. The second contribution is the creation of a process that uses agent-based traffic simulation in a more efficient way to target the most problematic links for analysis. The efficiencies gained from these two new ideas significantly reduce the amount of time and effort required to evaluate evacuation processes in large-scale networks at the agent level.

By rapidly narrowing down and ranking the list of possible most-critical links to a small, manageable size, the computational effort and time required to analyze individual links at a multi-city regional network level can be greatly reduced. For example, using the procedure described in this paper, an analyst could develop a candidate list of most-critical links from a network of tens of thousands within about 15 min. Currently, this type of assessment would take several weeks to complete using a traditional link-by-link simulation test method. Perhaps even more important is that the ranked list of critical links obtained from the performance index application was shown to be 64% statistically correlated to the ranking of the critical list developed from the simulations, particularly under the overwhelming demand created by an emergency evacuation.

Measures such as total travel time, total delay, and average and maximum number of queued vehicles are computed from simulations and used to compare network performance between various disruptive conditions that would prohibit travel on various links. To demonstrate this improvement, a case study of the Gulf Coast megaregion evacuation network is used.

With respect to time, the results of the case study show that a list of the most-critical links could be narrowed from the 34,000 links in the network to a set of top 50 critical links in 15 min. While it still takes approximately two weeks to run the simulations for the top 50 critical links, it is considerably faster than traditional methods. The time needed for this system of critical link identification and simulation to analyze a large evacuation network such as the Gulf Coast megaregion is overwhelmingly reduced.

The findings of this study could be useful for traffic engineers and emergency managers who are seeking to improve network resilience during hurricane evacuation. Identifying critical links can help prioritize infrastructure investments and help disseminate information in a timely manner to improve network resilience during disasters. For example, the Gulf Coast megaregion has the Manchac Swamp Bridge on I-55, as well as the Bonnet Carré Spillway bridge and the Atchafalaya Basin bridge along I-10, which are major evacuation routes in Louisiana. Before a hazardous situation arises, public authorities should ensure that alternative routes/connectors are available to evacuees living nearby and implement traffic monitoring at those locations to deal with disruptive events should they occur during the evacuation. The appearance of Braess' paradox in this research can also inform public authorities of possible locations to implement bridge or road closures during an evacuation to improve network flows and clearance times.

While this study represents an incremental step forward in research and could be applied to improve evacuation planning and traffic analysis for large-scale evacuations, it was subject to certain limitations. Firstly, this study does not consider the effects of multiple link closures on network performance. Among the most important next steps for future research are the consideration of the impact caused by compound disruptions and multiple link closures on network performance. Because natural disasters tend to close multiple adjacent links at a time, considering multiple link closures and the cascading effects of link closures and congestion propagation on the surrounding network will be an important advancement of this research. Another limitation is that this study assumes that drivers will always take the shortest path to their destination, but past studies suggest that other factors influence households' route choices in actual evacuation (e.g., route familiarity [*27–30*] and traffic management [*31*]). Further study on this aspect of driver routing behavior would be beneficial to improving traffic assignment models and simulations. A further limitation of this study was the lack of consideration of operational strategies for evacuations such as phased evacuations, which would also be a useful extension for this line of study. Finally, depending on the computation devices available, the simulation used in this study can still take several hours for each iteration, which could be a limitation for some. The application of artificial intelligence algorithms or other emerging computing technologies could be a method for future studies to continue to reduce the excessive computation times for simulations of large-scale transportation networks.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M Shapouri, J. Fuller; data collection: M. Shapouri; analysis and interpretation of results: M. Shapouri; J. Fuller; draft manuscript preparation: J. Fuller; B. Wolshon; N. Herrera. All authors reviewed the results and approved the final version of the manuscript.

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