



Effect of Disruptions on Megaregion Emergency Evacuation: A Pilot Study

Brian Wolshon, Mohammad Shapouri,

James David Fuller and Nelida Herrera

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16. Abstract The Gulf Coast region of the United States is increasingly vulnerable to a growing list of natural and manmade hazards. Mass evacuations are a fundamental protective action for the safety of the region; however, the complexity of such evacuations makes the rapid movement of people a complex task. This study introduces a performance index that ranks the criticality of each segment during a megaregion evacuation, which is then tested using simulation. It was found that links with higher exposure and fewer alternative paths are more critical, and these links' removal has an insignificant impact on clearance time This will help future emergency planners to identify bottlenecks during mass evacuations and make important decisions.			
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Chapter 1. Introduction

The southern coastal regions of the United States have a long history of impacts from numerous natural and manmade disasters. These events pose enormous risks to property, infrastructure, and most critically, the lives and health of vulnerable populations within these areas. Among the most critically impacted is the central Gulf Coast megaregion that stretches from New Orleans, Louisiana to Houston, Texas. This area is particularly at-risk since it is home to a vast number of industrial facilities, is crisscrossed by hundreds of rivers and other waterways, and it includes a population in excess of 10 million people that live, work, and vacation within 50 miles of the coast.

This combination of critical infrastructure assets of vital national interest, geographic exposure, and high population combine to create enormous vulnerabilities. Because not all risk to people and property can be eliminated or even mitigated through robust infrastructure protection, other forms of risk reduction must be included as part of hazard planning. One of the most effective in terms of cost and live-saving value is the use of mass evacuations to move near-coast populations when under immediate impending threats.

While often rapid and efficient, planning and managing evacuations in enormously and densely populated areas made up of multiple interconnected and overlapping metropolitan centers becomes very complicated as huge numbers are required to move in correspondingly complicated multiple, interconnected, and overlapping paths. Evacuation processes are often further impacted by common disruptive incidents like traffic accidents, mechanical breakdowns, and even on-going routine road maintenance that further limit the ability of regional infrastructure to accommodate the level of immediate, overwhelming, and distant travel demand created by such events.

This study explores methods to assess and evaluate emerging techniques to enhance the ability of megaregional highway traffic networks to absorb and recover from these complex yet frequently occurring evacuation-related disruptions. The research considers a wide range of disruptions, both large and small, and the way simple yet effective operation planning and infrastructure investment can be used to maximize the ability of emergency planners and transportation agencies to protect lives when faced with catastrophic disaster conditions.

While prior research has focused individually on the effects of traffic incidents^{1,2,3,4,5,6,7}, emergency evacuations⁸, and traffic patterns in megaregions⁹, few have focused on traffic incidents during evacuations¹⁰ or evacuations of megaregions⁹. Similarly, little if any prior research sought to examine the effects of disruptions on an evacuation scenario in a megaregion. This has created the need and opportunity for the research described in this paper to fill this gap by assessing the effect 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 usually to perform a traditional full-scan network analysis using traffic simulation. However, due to the large size and complexity of megaregion transportation networks, traditional simulation methods used to measure resiliency are unfeasible or time consuming. With that need in mind, this research introduces a novel performance index to describe the importance of each road segment in a megaregion network under evacuation settings. This index attempts to account for local effects of a road segment closure, the network-wide effects on flow and clearance time, as well as the topological and geometric configuration of the network.

The goal of calculating this proposed index for the entire network before simulation is to narrow down the search and produce a list of candidates for the most important or critical links in the

¹ Nagurney, A., Q. Qiang. (2007). Robustness of transportation networks subject to degradable links. *EPL80 68001*

² Sullivan, J.L., D.C. Novak, L. Aultman-Hall, and D.M. Scott. (2010). Identifying critical road segments and measuring system-wide robustness in transportation networks with isolating links: A link-based capacity-reduction approach. *Elsevier Ltd.*

³ Chen, B.Y., W.H.K. Lam, A. Sumalee, Q. Li, and Z.C. Li. (2012). Vulnerability analysis for large-scale and congested road networks with demand uncertainty. *Elsevier Ltd.*

⁴ Wang, D.Z.W., H. Liu, W.Y. Szeto, and A.H.F. (2016). Chow. Identification of critical combination of vulnerable links in transportation networks – a global optimisation approach. *Transportmetrica A: Transport Science.*

⁵ Gauthier, P., A. Furno, and N.E. El Faouzi. (2018). Road Network Resilience: How to Identify Critical Links Subject to Day-to-Day Disruptions. *Transportation Research Board.*

⁶ Li, F., H. Jia, Q. Luo, Y. Li, and L. Yang. (2020). Identification of critical links in a large-scale road network considering the traffic flow betweenness index. *PLoS ONE 15(4): e0227474.*

⁷ Gu, Y., X. Fu, Z. Liu, X. Xu, and A. Chen. (2020). Performance of transportation network under perturbations: Reliability, vulnerability, and resilience. *Elsevier Ltd.*

⁸ Murray-Tuite, P., B. Wolshon. (2012). Evacuation transportation modeling: An overview of research, development, and practice. *Elsevier, Ltd.*

⁹ Zhang, Z., N. Herrera, E. Tuncer, S. Parr, M. Shapouri, and B. Wolshon. (2020). Effects of shadow evacuation on megaregion evacuations. *Elsevier, Ltd.*

¹⁰ Hasan, S., R. Rahman. (2019). Assessing Crash Risks of Evacuation Traffic: A Simulation-based Approach. *SAFER-SIM University Transportation Center, University of Central Florida.*

network. The simulation can then be run for a predetermined number of top candidates from the newly developed list (for example, the top 50 links) instead of for every link in the network, which could be in the tens of thousands. In this way the effects of each link's removal can be examined and analyzed using different performance measures. These most important links can then be appropriately prioritized for use in future evacuation events to achieve maximum resilience across the network.

This paper is organized into 5 sections. In Section 2 a review of recent relevant literature related to network resilience, link criticality, traffic incidents, emergency evacuations, and megaregions is summarized. Next, in Section 3 the goals and methodological approach to carry out this study is described, including the introduction of the novel network performance index and data sources and collection. Then, in Section 4 the computational modeling results and cross-comparisons of the data categories is presented. Finally, the paper closes in Section 5 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.

Chapter 2. 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 on resiliency and link criticality. 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 megaregion areas. The use of the term was traced back to its scientific origins in order to understand how it relates to the current study of transportation network disruptions.

The concept of resilience was first introduced by ecologist C.S. Holling¹¹ in the context of the stability of ecological systems. In the intervening decades, resilience has been applied to many areas of study, such as economics, business management, computer science, urban structure, supply-chain management, and engineering. Due in part to an increased occurrence of disruptive natural disasters, terrorist attacks, and extreme weather events that severely affect large networks

¹¹ Holling, C.S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*.

of infrastructure, a need has arisen to apply the principles of resilience specifically to transportation engineering and traffic networks. Gu⁷ employs the definition of resilience of transportation networks as “the ability of a network to resist, absorb, adapt to, and recover from negative impacts of perturbations.” This information can be very useful for planners and policy-makers to ensure not only the proper preparation for large-scale disruptions and evacuations, but also the effective mitigation of common, everyday disruptions to the network as well as during emergency evacuation scenarios.

When a traffic network experiences such a perturbation or disruption, it causes an overall drop in network performance and a corresponding rise in overall travel costs. From small accidents to large natural disasters, a resilient network is one that provides adequate alternative paths for drivers and allows for a timely arrival at their destination even as the network is still recovering from the effects of a disruption. Transportation planners and city officials can also use resilience information to know which highways to prioritize in terms of maintenance and upkeep, and can even help in analyzing the effects of potential additions to the network (roads or additional lanes) for improved performance¹². Resilience is a multi-faceted concept that integrates several characteristics of a network, namely rapidity, resourcefulness, redundancy, and robustness. The rapidity of a network’s ability to recover is important in measuring resilience and describes how quickly a system regains its original level of functionality after a disturbance, also known as post-perturbation resilience⁵. Resourcefulness, the ability of a governing organization to identify disruptions and mobilize the appropriate resources also plays a large role in resilience, as well as redundancy, which describes the network’s availability of alternate routes. Perhaps the most important aspect of measuring resilience is the ability to mitigate hazards, known as pre-perturbation resilience or robustness⁵. Robustness describes the ability of a system to maintain a desired functionality level in the presence of a disruption. It has been measured with several indices which will be described in the next section.

Resilience has been measured in a number of ways and with a variety of indices and values. Gu⁷ used the following equation to describe the area under a curve depicting the performance of a

¹² Lou, Y. and L. Zhang. (2011). Defending Transportation Networks against Random and Targeted Attacks. *Transportation Research Record*.

network from the time of occurrence of a disruption until its return to full functionality. This as well as depictions of rapidity and robustness can be seen below in the corresponding figure of the resilience triangle in Figure 1:

- $RL = \int_{m_0}^{m_1} [100 - F(m)] dm$ (1)

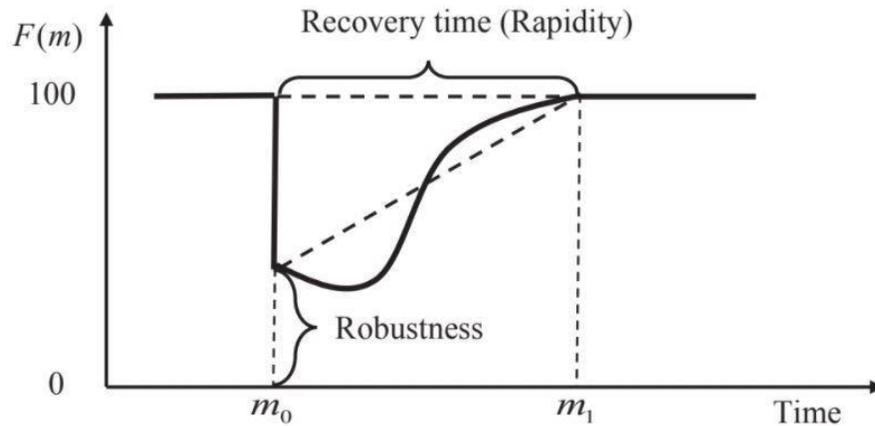


Fig. 1. Illustration of the resilience triangle. Adapted from [Bruneau et al. \(2003\)](#).

Although few studies have focused on the effect of disruptions during an evacuation, mitigating the effects of such disturbances is crucial to maintaining adequate evacuation flow and achieving a desirable clearance time for a hazard area. Some studies of evacuations focus on maximizing resilience and minimizing clearance time in evacuation scenarios^{13,14}. Others such as Reggiani¹⁵ and Ukkusuri¹⁶ used case studies and simulations to explore how connectivity plays an important role in the relationship between resilience and vulnerability. Lou¹² also explored resilience and

¹³ Zhang, Z., B. Wolshon, and P. Murray-Tuite. (2019). A conceptual framework for illustrating and assessing risk, resilience, and investment in evacuation transportation systems. *Elsevier Ltd*.

¹⁴ Tang, J., L. Zheng, C. Han, W. Yin, Y. Zhang, Y. Zou, and H. Huang. (2020). Statistical and machine-learning methods for clearance time prediction of road incidents: A methodology review. *Analytic Methods in Accident Research*.

¹⁵ Reggiani, A., P. Nijkamp, and D. Lanzi. (2015). Transport resilience and vulnerability: The role of connectivity. *Elsevier Ltd*.

¹⁶ Ukkusuri, S.V., W.F. Yushimito. (2009). A methodology to assess the criticality of highway transportation networks. *J Transp Secur*.

vulnerability in systems under random and targeted attacks by using optimization models. Some studies utilized sensitivity analysis as a basis for exploring network resilience^{17,18}.

As can be seen, there are many measures of resilience still being explored and developed. One of the most discussed topics relating to resilience in the body of literature is robustness, which describes the ability of a system to maintain a desired functionality level in the presence of a disruption. Robustness was the focus of a variety of studies on measuring resilience by means of various indices and relations. For example, several studies sought to use the network robustness index (NRI) as a significant indicator of network resilience. Some articles reviewed sought to measure robustness using their own methods^{1,3}, while several studies made more direct use of NRI values in their network analysis methodologies^{2,6}. However, a traditional full-scan NRI analysis is only feasible for smaller networks due to computational limitations. Several studies have sought to calculate the same list of critical link candidates as found by a full-scan analysis for larger networks without having to run a full simulation by means of novel indices^{5,6,19} or by innovative sampling and bounding techniques³.

Much of the research done on the identification of critical links in transportation networks has its roots in the sizable body of research on network vulnerability. Wang⁴ described vulnerability as “a kind of Achilles’ heel—a deadly weakness in spite of an overall strength that can potentially lead to a downfall.” Total travel time is a metric frequently used to gauge vulnerability and criticality in a network^{4,20}. Conversely, Knoop¹⁹ used a different set of indices to determine link vulnerability. These indices account for the effects of blocking/spillback of links, smaller/larger capacity links, and vehicle queueing. Chen³ developed a vulnerability index (VUL) which relates the efficiency of the network under normal conditions compared to when a link is removed. Taylor (2007) viewed vulnerability through the lens of reliability and accessibility to look specifically at the socio-economic impacts of degraded traffic networks.

¹⁷ Luathep, P., A. Sumalee, H.W. Ho, and F. Kurauchi. (2011). Large-scale road network vulnerability analysis: a sensitivity analysis based approach. *Transportation* 38.

¹⁸ Li, J. and K. Ozbay. (2012). Evaluation of Link Criticality for Day-to-Day Degradable Transportation Networks. *Transportation Research Record*.

¹⁹ Knoop, V.L., M. Snelder, H.J. van Zuylen, and S.P. Hoodendoorn. (2012). Link-level vulnerability indicators for real-world networks. *Elsevier Ltd*.

²⁰ Murray-Tuite, P.M., H.S. Mahmassani. (2004). Methodology for Determining Vulnerable Links in a Transportation Network. *Transportation Research Record*.

However, link criticality involves more than vulnerability indices. For example, centrality measures are a useful way to describe the relative positioning of nodes and links in complex networks and have been utilized more frequently in transportation network analysis in recent years^{5,21,22}. Betweenness centrality (BC) has become one of the most commonly used centrality measures to evaluate network traffic flow, describing the ratio of the number of shortest paths passing through a link (or node) to the total number of shortest paths in the network. Because this property is largely static in nature, several studies have sought to introduce dynamic characteristics of traffic flow into the equation^{21,22}.

The use of the shortest path problem (SPP) has been widespread since the introduction of Dijkstra's algorithm²³. Despite its common use and advancements made to its implementation, other studies highlight the limitations and shortcomings of the shortest path problem and how its usefulness has developed alongside other methods. Ukkusuri¹⁶ argued that the shortest path method was incapable of considering the effects of congestion on traffic networks, and both Gao²² and Manley²⁴ emphasized the discrepancy between shortest paths in a network and the actual route choices made by drivers. This uncertainty in driver behavior is shown as one of the biggest limitations to the effectiveness of the method. Even though they argue that the SPP more intuitively models route availability, Xu²⁵ and Gu⁷ even show how the existing algorithms for utilizing the shortest path method can be computationally intensive as well.

Although traditionally used in deterministic environments, the shortest path method has adapted in recent years due to a need for the method to consider the nondeterministic properties inherent to traffic networks²⁶. Uncertainties such as variable link travel times and driver route choice have limited the effectiveness of the shortest path method to accurately describe traffic flow on its own.

²¹ Kazerani, A. and S. Winter. (2009). Modified Betweenness Centrality for Predicting Traffic Flow. *University of Melbourne, Australia*.

²² Gao, S., Y. Wang, Y. Gao, and Y. Liu. (2013). Understanding Urban Traffic-Flow Characteristics: A Rethinking of Betweenness Centrality. *Environment and Planning B: Planning and Design*.

²³ Dijkstra, E.W. (1959). A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik 1*.

²⁴ Manley, E.J., J.D. Addison, and T. Cheng. (2015). Shortest path or anchor-based route choice: a large-scale empirical analysis of minicab routing in London. *Journal of Transport Geography*.

²⁵ Xu, X., A. Chen, and C. Yang. (2017). An Optimization Approach for Deriving Upper and Lower Bounds of Transportation Network Vulnerability under Simultaneous Disruptions of Multiple Links. *Elsevier Ltd*.

²⁶ Wu, L., W. Ma, Y. Yang, and K. Wang. (2017). A competitive analysis approach for route choice with uncertain travel times and blocked nodes. *Journal of Ambient Intelligence and Humanized Computing*.

Shang²⁷ also pointed out the need to bridge the gap between topological indices which describe the static, deterministic properties of a network, and operational indices which reflect the dynamic, nondeterministic nature of traffic flow. Broumi²⁸ also saw this need and affirmed that the SPP is “the heart of the network community,” and noted important related developments such as randomness and fuzziness that are helping bridge this gap. Wu²⁶ agreed that the shortest path problem is inappropriate in some scenarios but thought that the uncertainty theory proposed by Liu²⁹ was an effective way to consider uncertainty in an SPP. Other methods have also been proposed, for example Idri³⁰ introduced a time-dependent shortest path model that uses a cost function instead of constant cost values to achieve better performance while also maintaining an acceptable level of computation time, while Makariye³¹ used the SPP to help develop car navigation systems.

Although much of the research done on link criticality only considers single link failures, other studies considered the effects of multiple link failures^{4,32} or utilized the max cut min flow theorem³³. Rodríguez-Núñez³⁴ considered scenarios ranging from removal of one critical link up to the five most critical links to observe the percentage change in global travel times in the public transportation system of Madrid. Jenelius³² stressed the importance of redundancy importance which emphasizes links that might be commonly used as an alternative route in case other routes are blocked due to an accident, flooding, etc. These links may not usually carry large traffic flows, but if certain key links are not serviceable, these links play a huge role in mitigating the negative

²⁷ Shang, W.L., Y. Chen, C. Song, and W.Y. Ochieng. (2020). Robustness Analysis of Urban Road Networks from Topological and Operational Perspectives. *Mathematical Problems in Engineering*.

²⁸ Broumi, S., D. Nagarajan, A. Bakali, M. Talea, F. Smarandache, M. Lathamaheswari. (2019). The shortest path problem in interval valued trapezoidal and triangular neutrosophic environment. *Complex & Intelligent Systems*.

²⁹ Liu, B. (2007). Uncertainty Theory. 2nd ed. *Springer*.

³⁰ Idri, A., M. Oukarfi, A. Boumakoul, K. Zeitouni, and A. Masri. (2017). A new time-dependent shortest path algorithm for multimodal transportation network. *8th International Conference on Ambient Systems, Networks, and Technologies*.

³¹ Makariye, N. (2017). Towards Shortest Path Computation using Dijkstra Algorithm. *JNEC, Dr. B.A.M. University*.

³² Jenelius, E. (2010). Redundancy importance: Links as rerouting alternative during road network disruptions. *Elsevier Ltd*.

³³ Abdullah, N. and Hua, T. K. (2017). Using Ford-Fulkerson Algorithm and Max Flow-Min Cut Theorem to Minimize Traffic Congestion in Kota Kinabalu, Sabah. *Journal of Information System and Technology Management*

³⁴ Rodríguez-Núñez, E. and J.C. García-Palomares. (2014). Measuring the vulnerability of public transport networks. *Elsevier Ltd*.

effects of such disruptions. This is very useful in the consideration of multiple link closures and which network members' removals constitute a worst-case scenario for traffic flow.

An important area of study in network flow to arise is the Max Cut Min Flow Theorem. Heavily based on studies by Ford³⁵ and Edmond³⁶, Shengwu³⁷ used this idea to identify bottleneck locations in the traffic network of Jilin City, China. The theorem uses the Ford-Fulkerson and Edmonds-Karp algorithms to make strategic cuts across a network in order to determine the maximum amount of flow the network is capable of transporting. Using the data collected, cities and regions can better determine the best location to add a new road segment to mediate traffic congestion. Abdullah³³ used a similar approach in Kota Kinabalu, Sabah, Malaysia, which highlights the flexible and user-friendly nature of the Ford-Fulkerson algorithm.

As can be seen, a growing body of knowledge about the resilience of transportation networks and critical link analysis has developed and continues to push forward. While many studies have described the effects of traffic disruptions on network performance, only a few have focused on disruptions during evacuation scenarios or in megaregion areas. Many indices have been used to quantify various aspects of complex network performance. Although some general consensus has been reached on the general meanings of terms like resilience, robustness, criticality, and vulnerability, there is still no universally decided-upon standard definitions. This study aims to fill the gap in the existing literature exploring the determination of critical links and their removal's effect in an evacuation scenario.

Chapter 3. Methodology

Due to 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 through the use of a

³⁵ Ford, L.R. and D.R. Fulkerson. (1956). Maximal Flow Through a Network. *Canadian Journal of Mathematics*.

³⁶ Edmonds, J. and R.M. Karp. (1972). Theoretical Improvements in Algorithmic Efficiency for Network Flow Problems. *Journal of the ACM*.

³⁷ Shengwu, D. and Z. Yi. (2011). Research on Method of Traffic Network Bottleneck Identification Based on Max-flow Min-cut Theorem. 2011 *International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE)*.

new performance index. This index is composed of multiple terms which have either been newly developed or adapted from commonly used measures. This index can be used to analyze properties of networks without needing the time 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 $i = 1, 2, 3, \dots, n_L$, and each node n_j is labeled such that $j = 1, 2, 3, \dots, n_N$. 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^* upon its removal from the network. This set contains n_P paths, and each path p_r is labeled such that $r = 1, 2, 3, \dots, n_P$.

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} . 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 due to 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 use 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 removal are marked by a superscript b , and those calculated after a link removal are written with a superscript a . Flow volumes are determined using the User Equilibrium model, and the travel costs are computed using the Bureau of Public Roads function, both of which are described below.

3.1. User Equilibrium and BPR Function

User Equilibrium (UE) is a traffic assignment model has been used that seeks to apply origin-destination (O/D) demand pairings to a network and assign individual vehicles to paths that will

minimize travel costs. This principle was developed by Wardrop³⁸, who described equilibrium as a “situation in which no driver can reduce his journey time by choosing a new route.” This is usually achieved through the application of demand pairings to a network in an iterative process that eventually converges to a solution. This can be achieved in numerous ways, and various approaches have been explored in the decades since its introduction.

Many forms of User Equilibrium have been developed, differing in the assumptions made about driver knowledge, goals, and behavior. Zhang³⁹ describes the difference between deterministic user equilibrium (DUE), stochastic user equilibrium (SUE), boundedly rational user equilibrium (BRUE), and behavioral user equilibrium (BUE). DUE assumes that all drivers have perfect knowledge of the network and its attributes and that all drivers share the same preferences and goals of utility maximization for all vehicles across the network. While not very realistic, this model is stable and widely available to researchers. SUE incorporates random perception errors to the model to account for drivers’ imperfect knowledge of the network. BRUE replaces utility maximization with satisficing behaviors - decisions drivers deem to be “good enough” to satisfy a certain threshold. Finally BUE seeks to overcome the shortcoming from BRUE by using positive SILK theory, which is a travel behavior theory that emphasizes search, learning, and knowledge in pathfinding.

The link performance function used to calculate travel time was developed by the Bureau of Public Roads (BPR) in 1964 as a way to help reduce the computation burden of existing techniques. The BPR function used is shown below:

$$\bullet \quad K_{l_i}(V_{l_i}) = t_{l_i}^0 \left[1 + \alpha \left(\frac{V_{l_i}}{C_{l_i}} \right)^\beta \right] \quad (2)$$

where $K_{l_i}(V_{l_i})$ is the total travel time across link l_i , $t_{l_i}^0$ represents the free-flow travel time across link l_i , V_{l_i} denotes the flow of link l_i , and C_{l_i} is the capacity of link l_i . The remaining parameters α and β are commonly taken to be 0.15 and 4 respectively, and these are the values that this study uses.

³⁸ Wardrop, J.G. (1952). Some Theoretical Aspects of Road Traffic Research. *Proceedings of the Institute of Civil Engineers*.

³⁹ Zhang, Lei. (2011). Behavioral Foundation of Route Choice and Traffic Assignment. *Transportation Research Board*.

Once the network demand has been loaded and link travel costs have been calculated and the network has been loaded, the criticality of each link found in a shortest path can be examined by the implementation of the proposed index. This index is a combination of newly developed concepts and adaptations of 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. Although they approach this problem from different angles, all terms involved are based on established methods for network analysis.

3.2. Shortest Path Problem

Shortest path problems (SPPs) are an important part of network flow optimization, and a large body of literature has developed around the subject. First introduced by Dijkstra²³, shortest path trees are an effective method for determining the shortest path from a particular node to all other nodes in the network. This idea has come to play a prominent role in transportation engineering as researchers have sought to use the Dijkstra algorithm to optimize traffic flows and develop relevant metrics to measure traffic network performance. The algorithm can be used to analyze the R number of shortest paths between each O/D pair, and in this study, we will use $R = 1$ because we are only considering the single shortest path between each O/D pair to reduce the computational burden. Over the years, the SPP has been implemented in a wide variety of ways, from significantly reducing computational burdens⁴⁰ to measuring properties like connectivity, betweenness, network efficiency, and mean geodesic distance between nodes⁴¹.

3.3. Index Equation and Definition of Terms

The proposed index will now be introduced and examined in more detail. As previously stated, links that are considered more critical will produce a higher value, and a less critical link will return a smaller value. The formula is as follows:

⁴⁰ Jenelius, E., T. Petersen, and L.G. Mattsson. (2006). Importance and exposure in road network vulnerability analysis. *KTH/Royal Institute of Technology*.

⁴¹ Grubestic, T.H., T.C. Matisziw, and A.T. Murray. (2008). Comparative Approaches for Assessing Network Vulnerability. *International Regional Science Review*.

$$\bullet \text{ Index}_{l_i} = (AP_{l_i}^{norm} + MF_{l_i}^{norm} + BC_{l_i}^{norm}) * (\lambda_{l_i}^{norm}) \quad (3)$$

where $AP_{l_i}^{norm}$ is the normalized alternative path term for link l_i , $MF_{l_i}^{norm}$ is the normalized maximum flow term for link l_i , $BC_{l_i}^{norm}$ is the normalized betweenness centrality of link l_i , and $\lambda_{l_i}^{norm}$ is the normalized exposure factor for link l_i . Each of these terms is normalized before being used in the equation.

3.3.1. Alternative Path Term

When a driver encounters a disrupted link along their route during an evacuation, an alternate path must be found if they are 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 due to 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).

This study defines a term that describes the criticality of link l_i not only by the number and availability of viable alternative paths, but by the ability of those alternative paths to efficiently reroute and accommodate the flow of link l_i after its removal from the network with as little damage to network performance possible. Drivers mostly tend to return to their original route when facing disruptions, if it is available⁴², so the index seeks to recreate this situation in a small representative scenario. 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 ratio. 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/C ratios are calculated for the mini-system before and after the removal of link l_i^* and the difference between the two are measured. This value is then related to the modified count of unique alternative paths available to find a final value for link l_i . This is shown in detail via the following equation:

⁴² Koo, R. & Y. Yim. (1998). Commuter Response to Traffic Information on an Incident. *Transportation Research Record*.

$$\bullet \quad AP_{l_i} = \left(\frac{V_{l_i} + \sum_{p=1}^{n_p} \Omega(k_{l_i}^p) v_{l_i}^p}{\delta_{l_i} c_{l_i} + \sum_{p=1}^{n_p} \Omega(k_{l_i}^p) c_{l_i}^p} - \frac{V_{l_i} + \sum_{p=1}^{n_p} \Omega(k_{l_i}^p) v_{l_i}^p}{c_{l_i} + \sum_{p=1}^{n_p} \Omega(k_{l_i}^p) c_{l_i}^p} + \delta_{l_i} \right) * \frac{1}{n_p^*} \quad \forall p \in P^* \quad (4)$$

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), $\Omega(k_{l_i}^p)$ 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 zero if link l_i^* is a non-isolating link or is equal to one if link l_i^* is an isolating link.

The term $\Omega(p)$ was included to represent the probability of a driver to choose one alternative path over another based on their estimated travel costs, $k_{l_i}^p$. When link l_i^* is disrupted and removed from the network, its traffic flow volume must be redistributed among the alternate paths available. If one alternative path is clearly much more costly than another, few 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 in more exact terms, the following multinomial logit model was utilized:

$$\bullet \quad \Omega(p) = \frac{e^{-\alpha k_{l_i}^p}}{\sum_{p=1}^{n_p} e^{-\alpha k_{l_i}^p}} \quad \forall p \in P^* \quad (5)$$

where $k_{l_i}^p$ is the travel cost of a certain alternative path choice and α is a constant that must be calibrated for each network examined. If α is too high, drivers will have a 100% chance of using the alternative path with the least cost, regardless of the costs of other alternatives. If α is too low, drivers will be evenly split across all alternatives, regardless of the costs. The desired value in between these two extremes varies from situation to situation and 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. However, since some paths may have drastically different travel costs, counting these paths equally could easily overestimate the

options available to drivers. If a driver is faced with one short alternative path and one very long alternative path, it can be misleading to consider those two paths equally viable - especially in comparison to another link where a driver is faced with two paths of similar travel cost. Also considered was the magnitude of the difference between the travel costs of the alternative paths available and the original disrupted link. These factors are expressed by the following equation:

$$\bullet \quad n_p^* = 1 + \frac{K_{l_i}}{\sum_{p=1}^{n_p} k_{l_i}^p} \quad \forall p \in P^* \quad (6)$$

where K_{l_i} is the use travel cost of link l_i , and $k_{l_i}^p$ is the travel cost of each path alternative to l_i .

If alternative paths exist upon the removal of a link from the network, that link is said to be non-isolating. In the case of a non-isolating link's removal, its index can be calculated using the following simplified version of the index equation:

$$\bullet \quad AP_i = \left(\frac{V_i + \sum_{p=1}^{n_p} \Omega(k_i^p) v_i^p}{\sum_{p=1}^{n_p} \Omega(k_i^p) c_i^p} - \frac{V_i + \sum_{p=1}^{n_p} \Omega(k_i^p) v_i^p}{C_i + \sum_{p=1}^{n_p} \Omega(k_i^p) c_i^p} \right) * \frac{1}{n_p^*} \quad \forall p \in P^* \quad (7)$$

This focuses the value on the effect of the link's removal on the cumulative V/C ratio among the alternative paths available.

The equation simplifies considerably if the link considered is an isolating link. i becomes 1 and the equation adjusts in two ways. First, the addition of C_i to the denominator of the first fraction makes both fractions equal, giving a difference of zero. This in turn means the whole term in parentheses will equal 1. This just leaves the ratio of this term to the modified path count, which in the case of an isolating link is also equal to one. Therefore the AP index for isolating links is always one.

3.3.2. Maximum Flow Term

While the Alternative Path term considers the local effects of link closures, the maximum flow term seeks to describe the system-wide effects of link removal on the network. Calculating the maximum number of cars that can travel across a network during a given time period is an important network characteristic to consider, especially in evacuation situations. Knowing just how many people a system can efficiently remove from harm's way, where bottlenecks occur, and

how much they limit flow can help planners and administrators make important decisions regarding emergency preparedness and infrastructure investment. This paper introduces a Maximum Flow term which seeks to quantify and rank the effect of a link's removal on the maximum flow of traffic possible across the network from a source node to a sink node.

This method is an effective way to identify bottleneck locations in the network and can be a helpful tool in mitigating areas prone to congestion. Because bottlenecks are areas of relatively low performance, this method seeks to find the disconnecting set with the lowest cumulative flow capacity. This location denotes the network bottleneck, and therefore this value equals the maximum flow possible through the whole network for the origin-destination pair. Care must be made to only count capacities of links moving from the sub-network the origin and towards the sub-network containing the destination.

This Maximum Flow term seeks to describe a link's impact on the maximum network flow upon its removal. The max flow values of each O/D pair are determined before and after the iterative removal of each link being examined. The larger the difference in maximum flow values from before link removal to after link removal gives a higher value index, indicating a higher level of criticality. Summing these values aggregates the negative impacts a link's removal has across all O/D pairs. This process is represented by the following equation:

$$\bullet \quad MF_{l_i} = \sum_{\pi \in \Pi} n_{\pi} \left(\frac{\phi_{l_i}^b - \phi_{l_i}^a}{\phi_{l_i}^b} \right) \quad \forall w \in W \quad (8)$$

where $\phi_{l_i}^b$ is the max flow for O/D pair w before the removal of link l_i^* , and $\phi_{l_i}^a$ is the max 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.

3.3.3. Betweenness Centrality Term

Betweenness centrality describes the ratio of the shortest paths passing through a link (or node) to all the shortest paths in the network. This was a very useful development in the field of complex

network theory and graph theory and has come to be used by transportation engineers as a method for identifying the criticality of network components. However, since this original definition is purely topological in nature, it is not capable of considering the effects of traffic flow across the network and its effect on the criticality of a link or node.

This study seeks to utilize this term in conjunction with the two previously described terms to obtain a well-rounded perspective on network performance. Since the Alternative Path and Maximum Flow terms are highly involved in the dynamic aspects of traffic flow, including a more topologically oriented term is appropriate. The equation for the betweenness centrality term is as follows:

$$\bullet \quad BC_{l_i} = \frac{\sum_{\pi \in \Pi} \mu_{\pi}}{n_w} \quad \forall w \in W \quad (9)$$

where n_w is the estimated number of origin-destination 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.

Li⁶ used a similar idea to develop a Traffic Flow Betweenness index that considered both static and dynamic properties of a network. However, the equation utilized by Li considers the number of times a link lies in the shortest path of O/D pairs compared to the total number of shortest paths in the network, not the total number of O/D paths. By limiting the number of paths used in the denominator to the total number of O/D pairs, the data should not be inaccurately skewed by large numbers of unused paths in the network that do not affect the O/D paths being evaluated.

3.3.4. Exposure Term (λ)

The final term describes the probability that an incident will happen on the link in consideration during the evacuation. In the same way that Jenelius³² demonstrated in their disruption analysis, length was used as a crude indicator of disruption probability. The calculation of the exposure factor is as follows:

$$\bullet \quad \lambda_{l_i} = \left(\frac{x_{l_i}}{\bar{x}} \right) \left(\frac{v_{l_i}}{v_{total}} \right) m_{l_i} \quad \forall l_i \in L \quad (10)$$

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 how many lanes of unidirectional traffic are available across link l_i . If considering the length of the link is important in incident probability, it follows that number of lanes would also be important to include. Adding a second lane of travel in the same direction introduces not only more surface area for incidents to occur, but also multiple new conflict points that did not previously exist. This value is then multiplied by the volume fraction so that links carrying a greater amount of traffic will be considered more critical than links carrying fewer vehicles. 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.

3.4. Case Study

The transportation network being analyzed in this study is the US Gulf Coast Megaregion that stretches 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 2, was developed using ArcMap 10 GIS software⁹. The figure also shows the projected hurricane track causing the evacuation, determining the current demand loading to be applied.

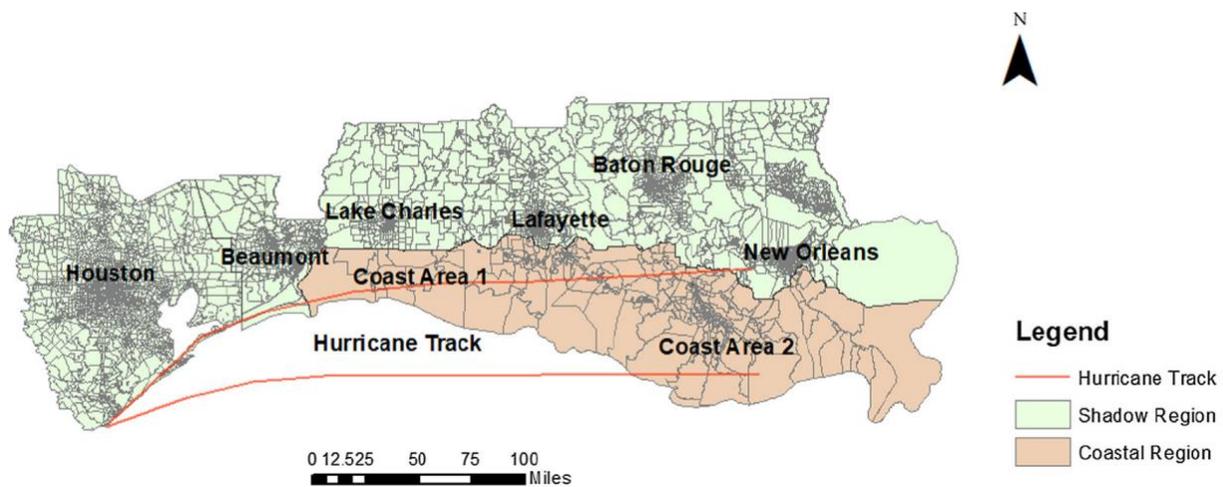


Figure 2. Map of megaregion network and hurricane track.

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 in 1867. For more details regarding the development of TRANSIMS model readers are referred to⁹. The generated demand consisted of the following: 546,780 vehicles in the Houston area, 41,689 vehicles in Beaumont, 25,809 vehicles in Lake Charles, 27,936 vehicles in Lafayette, 109,019 vehicles in Baton Rouge, 206,595 vehicles in New Orleans, 29,327 vehicles in Coast Area 1, and 27,917 vehicles in Coast Area 2. Next, to assess the effect of link removal on the traffic network during evacuation, links with the highest index values are considered to be candidates for the most critical links in the system and are iteratively removed in the model. The outputs will be presented and analyzed in the following section.

Table 1. Topological details of megaregion network.

City	Number of Nodes	Number of Links	Average Node Degree	Average Link Degree	Average Node Betweenness	APL	D
Megaregion	23297	34586	2.9691	4.47	0.0042	----	----
Houston	12116	17161	2.8328	4.32	0.0041	51.816	160
Beaumont	3716	5607	3.0178	4.46	0.0101	38.452	105
New Orleans	2693	4364	3.2410	4.90	0.0088	24.730	38
Baton Rouge	1205	1870	3.1037	4.57	0.0147	18.968	46
Lake Charles	1149	1839	3.2010	4.80	0.0141	17.278	38
Lafayette	869	1390	3.1991	4.68	0.0187	17.251	45

Table 2. Demand loading in each network area (vehicles)

Network Area	Demand	Network Area	Demand
Houston	546,780	Baton Rouge	109,019
Beaumont	41,689	New Orleans	206,595
Lake Charles	25,809	Coast 1	29,327
Lafayette	27,936	Coast 2	27,917

Chapter 4. Results

Once the performance index has been defined, it can be applied to each link along O/D shortest paths in a large-scale network. The higher the value associated with a link, the more critical it is considered to be 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.

4.1. Developing List of Critical Link Candidates

After applying the index, the links were ranked according to the calculated values. These links are highlighted on the map in Figure 3, with (a) showing the locations of the top 10 candidates, and with (b) showing the top 50 candidates across the network. These links lie largely along the main interstate and highway corridors heading both east-west and north-south, many of which coincide with segments designated by authorities as hurricane evacuation routes. These corridors usually carry high traffic volumes, especially during evacuations, with very few alternate routes available, if any. Especially in southern Louisiana where there are many bridges, a disturbance on many of these road segments could leave travelers with no alternative routes to their destination. This situation would likely return a high index value. Due to the importance of exposure to disruptions during evacuations, main highways also have a higher rank in the list. 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 mainly from Lake Charles to New Orleans and why none are found west of Beaumont. Also notable are the inclusion of several north-south routes leading away from the coast. When a tropical weather system approaches land, one of the most important and instinctual actions to take is to move people inland, away from low

lying coastal areas threatened by the worst of the wind, rain, and storm surge.

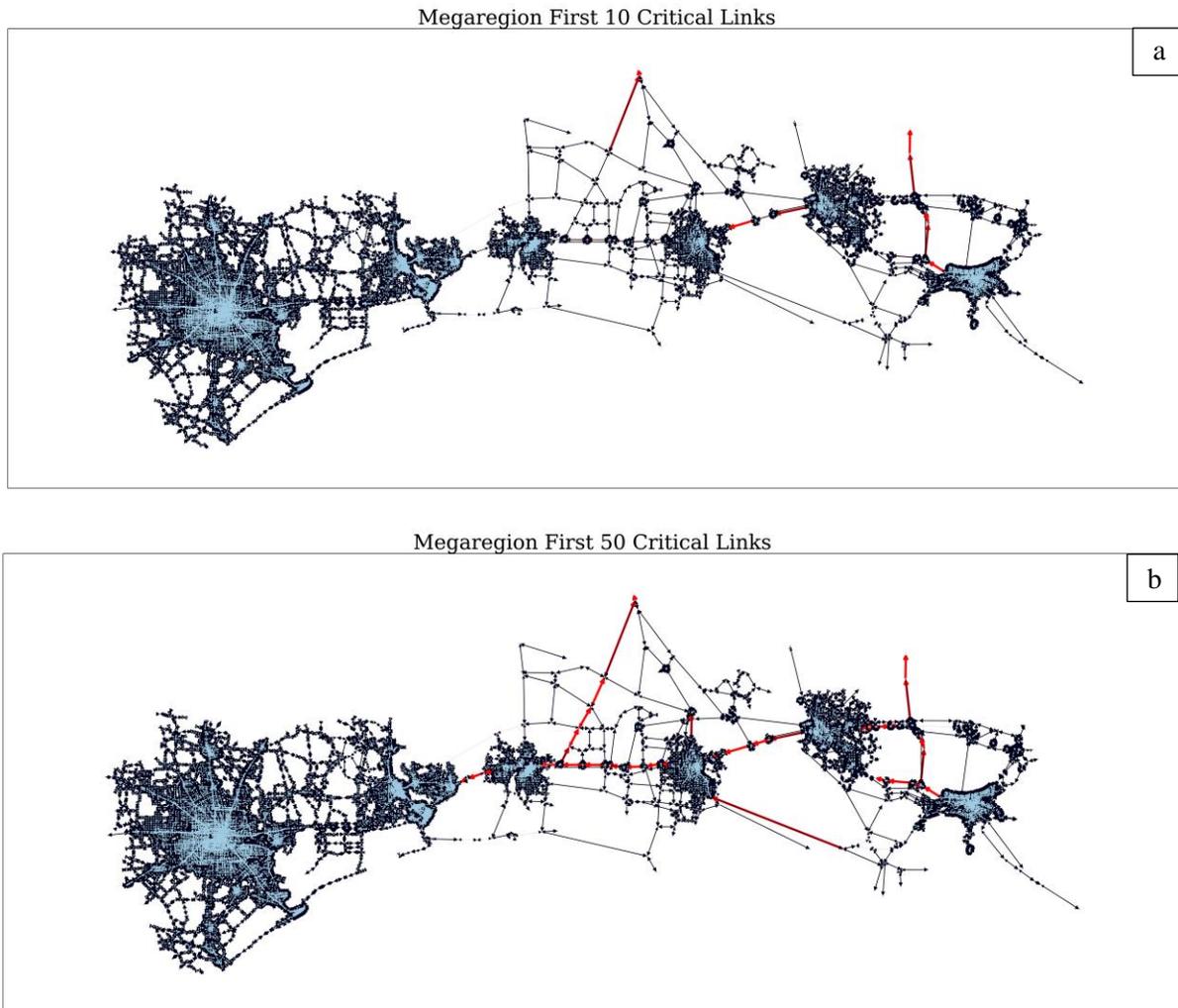


Figure 3. Map of megaregion network showing location of top 10 (a) and top 50 (b) critical link candidates

Therefore, evacuation routes running perpendicular to the coastline become very important in moving people out of harm's way. Segments of Interstate 55 North, I-110N, I-49N, and US-165N are all emphasized as critical to network performance. However, it should be noted that due to the configuration of our network and the simplified representations of the road networks in destination cities at the edges of the network such as Alexandria, Louisiana might contribute to an overestimation of the criticality of links near the extreme edges of the network.

4.2. Traffic Simulation

To verify the findings of our performance index, the outputs from traffic simulation is analyzed. The simulation results represent an average of 20 individual model iterations, and each scenario run takes approximately 10 hours with a loading of 60% of demand. Because of the duration of each simulation run, it would take years to perform this task if we included every link in the network, 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. Performance measures such as vehicle hours of travel, vehicle hours of delay, average queued vehicles and maximum queued vehicles were generated by the simulation software. These performance measures were produced first for a base case scenario where the full network is considered with no link removals. Then the top critical link candidates were iteratively removed from the network, and the same performance measures were generated and collected for each case. This data can be seen below in Table 3. The removal of each link causes an increase in hours of vehicle travel and delay, as well as an increase in the number of queued vehicles. It can be seen that links toward the top of the candidate list cause large 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 for each of these performance measures for the top 50 candidate links are represented graphically in Figures 4(a)-(d).

The data for the top fifty candidate links was then reorganized to show which links caused the overall largest change in the performance measures observed by TRANSIMS. This was achieved by averaging the percentage change in each of the performance measures for each link and sorting the list from highest values to lowest. This data is reflected below in Table 4. The first set of columns show the already established list of top 15 candidate links found using the proposed performance index, while the second set shows the top 15 links sorted by average change in performance measures. Note that the set of links contained in the top ten ranks of each list are identical, but in a slightly different order. The top ranked links for average travel time in Figure 4(a) (link 8, 4, 9, and 1) are all found in the same order atop the newly ranked list. Also, the Spearman rank correlation between first 50 links in terms of impact and the top 50 candidates

shows a good correlation with $\rho=0.643$. This information also helps to affirm the usefulness of the proposed performance index.

Table 3. Performance measures of base case and top 15 candidate link removals from simulation

Rank	Vehicle Hours of Travel	Vehicle Hours of Delay	Avg. Queued vehicles	Max Queued vehicles
Base Case	716122.1	169950.37	85130.33	181920
1	759358.78	225486.45	133578.9	234176
2	754737.27	220149.41	130874.8	231891
3	749730.28	213014.97	128985.6	229929
4	769609.97	232284.12	137480.8	252005
5	746052.38	212004.88	125094.2	221014
6	745642.31	208987.33	119987.3	219045
7	740922.99	204764.79	113987.8	218438
8	768321.9	230538.27	135113.6	248352
9	771091.74	238865.85	127473.2	244023
10	733978.28	190982.71	106971.5	212939
11	731679.44	187329.99	96863.83	197552

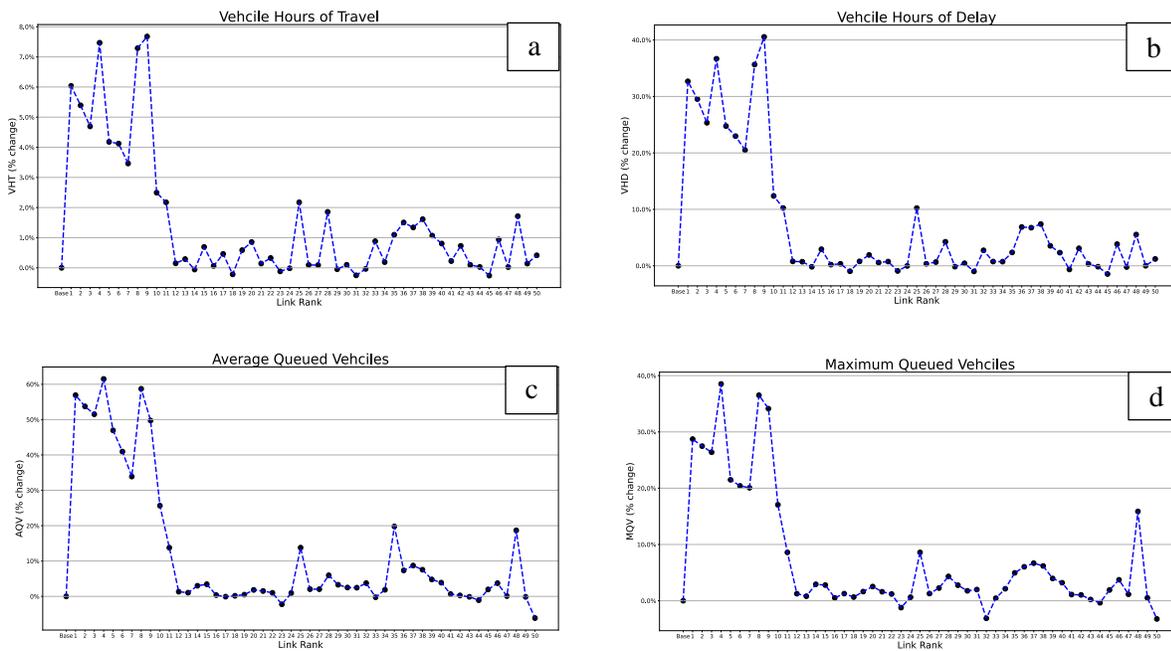


Figure 4. Performance measures of top 50 critical link candidates in terms of percentage change in (a) vehicle hours of delay, (b) vehicle hours of travel, (c) avg. queued vehicles, and (d) max. queued vehicles

This data is also reflected in Figure 4, where these same links are frequently the highest values to be seen. Figure 5(b) generated a less dramatic distribution of values. Because this is an evacuation scenario, the vast majority of people in the network are moving in the same directions (north and west, denoted A-B) and not in the opposite directions (south and east, denoted B-A). This is reflected in which links have the greatest impact on network performance. While the magnitude of the difference between the base case and the largest disruption appears on this map as only 2-3 minutes, this value was averaged from among all of the vehicles across the entire region, which adds up to significant and costly reductions in network performance.

Table 4. Performance measures of base case and top 15 candidate link removals from simulation

Rank	Link Number	Index Value	Normalized Index value	Rank	Link Number	Avg Percentage Performance change
1	55290	0.2141	1.0000	1	54965	32.39513
2	16977	0.1890	0.8829	2	54967	32.20852
3	55299	0.1408	0.6576	3	55304	28.4531
4	54965	0.0979	0.5105	4	55290	28.23736
5	5599	0.0821	0.3834	5	16977	24.86014
6	7499	0.0716	0.3346	6	55299	23.31196
7	55296	0.0673	0.3143	7	5599	20.91051
8	54967	0.0672	0.3103	8	7499	18.53229
9	55304	0.0667	0.3100	9	55296	15.37926
10	16404	0.0663	0.3096	10	16404	12.41196
11	16889	0.0576	0.2692	11	305	8.995167
12	19282	0.0548	0.2560	12	16889	8.199116
13	54452	0.0527	0.2464	13	55324	8.199116
14	19387	0.0466	0.2177	14	544	7.474998
15	16817	0.0433	0.2024	15	9952	6.624447

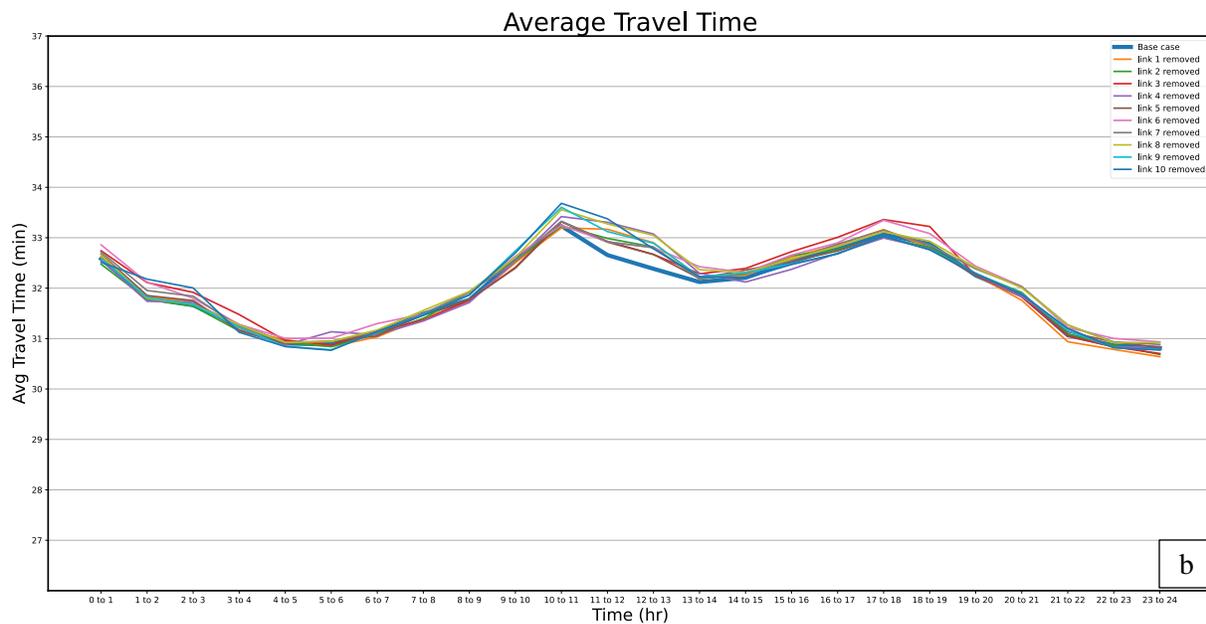
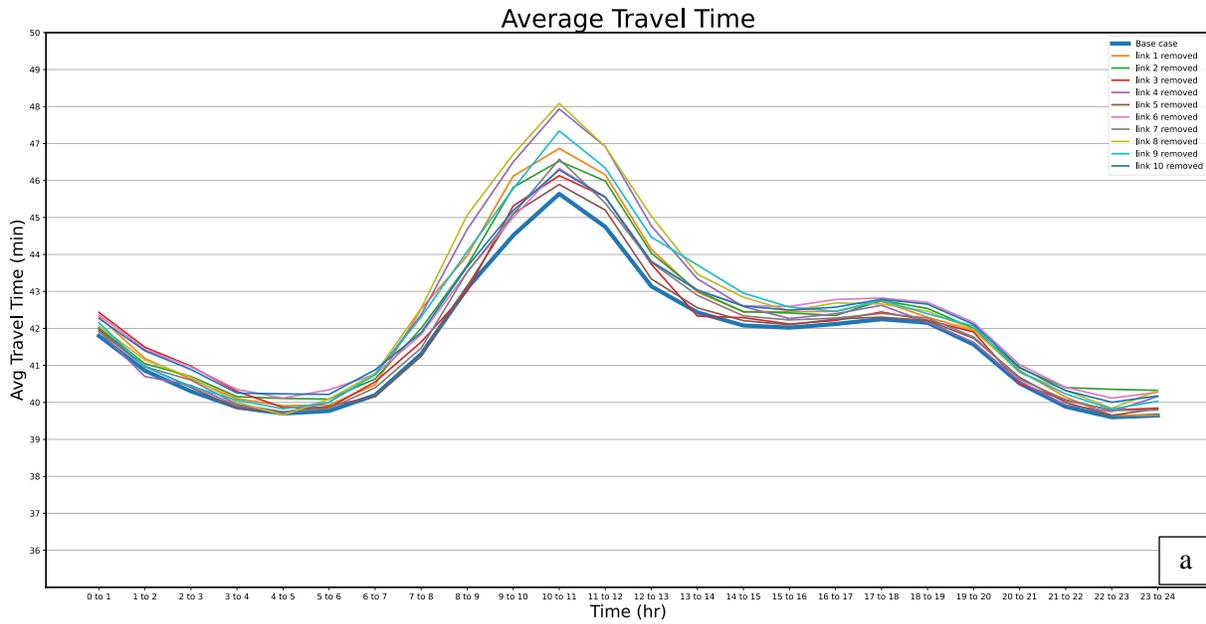


Figure 5. Graph of average travel time across megaregion network for (a) the primary direction (A-B) and (b) the reverse direction (B-A)

An important question to ask about these increases in vehicle travel time is what effect these link removals have on the overall clearance time of the network for the entire duration of the evacuation. Figure 6 shows the cumulative percentage of vehicles evacuated for each simulated run compared to that of the base case over 24 hours. Here the base case has the highest values throughout the process. For the first few hours of the evacuation in the early morning hours, total

clearance was nearly identical for all scenarios. The only significant deviations occur during the hours of 6:00-16:00, the same time span that showed pronounced increases in average travel time in Figure 5(a). From 16:00 until the end of the evacuation, all data sets converge once again to near equal levels. Therefore during the busiest hours of the evacuation, travel times increase and hinders more people from leaving the network. However, as the congestion subsides and travel times reduce after 16:00, clearance times return to those of the base case scenario. So although link disruptions damage network performance for a busy period during the evacuation, overall clearance times are not affected.

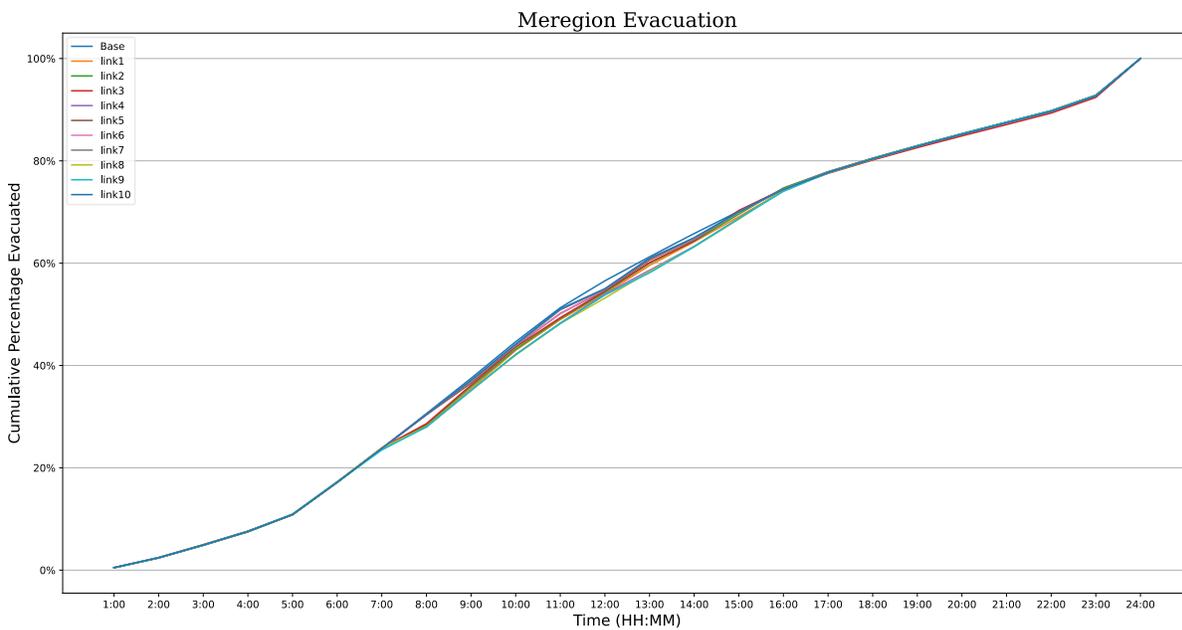


Figure 6. Graph showing clearance times for duration of evacuation from each simulation run.

Chapter 5. Conclusion

The goal of the research described in this paper was to enhance evacuation planning, particularly mass evacuations in multicity megaregional areas. The contributions of this work were two-fold. The first was the development of a novel computational process to systematically assess evacuation megaregional roadway networks to identify critical links that, if restricted or closed, would most-adversely affect a mass evacuation process. In addition to quantifying and ranking each link based on its traffic flow criticality, the second significant contribution of this research is the application of the process to create a tool to compute the overall resilience of the network

through the generation of a resilience index which considers both the static and dynamic properties of traffic flow across a transportation network. The computational effort required to completely analyze individual links in multistate megaregional networks can often require weeks, if not months of effort. By adapting the process described here, the new index can significantly shorten this time to minutes by rapidly narrowing down and ranking the list of network links to a small, manageable size of specific “links-of-interest” to be analyzed in more detail. This process achieves more accurate and reliable results than any existing tools, particularly for demand loadings during emergency evacuations.

Using megaregional scale microscopic traffic simulation, the resilience index was shown to consider network topology, risk of link disruption, and traffic flow characteristics into its calculation. Once the candidate list of most-critical links was developed and ranked, the impact of each link removal was measured using a TRANSIMS simulation. The link-removal process showed a statistically significant correlation between the candidate list and the performance measures found in the simulation. Other measures such as total and average travel times and well as average and maximum number of queued vehicles showed interesting results.

A particular notable finding of the evaluation was that the most impactful link removals in the test network in terms of average travel time showed the most significant effects occurred during the hours of 6:00AM to 4:00PM. When analyzing network clearance times over the same 24-hour evacuation, this same time span shows the greatest impact upon link removal. However, despite delays during the peak hours of flow, the effect on overall network clearance time was negligible. Combined, these results suggest that links with higher exposure to disruptions and fewer alternative paths have a higher impact on network resilience during evacuation while the overall effect of disruption on clearance time is insignificant.

While this study represents an incremental step forward in research and will likely have significant application potential in large-scale evacuation planning and traffic analysis, further development and study are needed. Among the most important next steps is the consideration of the impact caused by multiple link closures on network performance and resilience and considering weights on individual terms in the proposed index.

References

- Nagurney, A., and Q. Qiang. (2007). Robustness of transportation networks subject to degradable links. *EPL80 68001*. Retrieved from <https://iopscience.iop.org/article/10.1209/0295-5075/80/68001>
- Sullivan, J.L., D.C. Novak, L. Aultman-Hall, and D.M. Scott. (2010). Identifying critical road segments and measuring system-wide robustness in transportation networks with isolating links: A link-based capacity-reduction approach. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.tra.2010.02.003>
- Chen, B.Y., W.H.K. Lam, A. Sumalee, Q. Li, and Z.C. Li. (2012). Vulnerability analysis for large-scale and congested road networks with demand uncertainty. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.tra.2011.11.018>
- Wang, D.Z.W., H. Liu, W.Y. Szeto, and A.H.F. (2016). Chow. Identification of critical combination of vulnerable links in transportation networks – a global optimisation approach. *Transportmetrica A: Transport Science*. Retrieved from <https://doi.org/10.1080/23249935.2015.1137373>
- Gauthier, P., A. Furno, and N.E. El Faouzi. (2018). Road Network Resilience: How to Identify Critical Links Subject to Day-to-Day Disruptions. *Transportation Research Board*. Retrieved from <https://doi.org/10.1177/0361198118792115>
- Li, F., H. Jia, Q. Luo, Y. Li, and L. Yang. (2020). Identification of critical links in a large-scale road network considering the traffic flow betweenness index. *PLoS ONE 15(4): e0227474*. Retrieved from <https://doi.org/10.1371/journal.pone.0227474>
- Gu, Y., X. Fu, Z. Liu, X. Xu, and A. Chen. (2020). Performance of transportation network under perturbations: Reliability, vulnerability, and resilience. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.tre.2019.11.003>
- Murray-Tuite, P., B. Wolshon. (2012). Evacuation transportation modeling: An overview of research, development, and practice. *Elsevier, Ltd*. Retrieved from <http://dx.doi.org/10.1016/j.trc.2012.11.005>
- Zhang, Z., N. Herrera, E. Tuncer, S. Parr, M. Shapouri, and B. Wolshon. (2020). Effects of shadow evacuation on megaregion evacuations. *Elsevier, Ltd*. Retrieved from <https://doi.org/10.1016/j.trd.2020.102295>

Hasan, S., R. Rahman. (2019). Assessing Crash Risks of Evacuation Traffic: A Simulation-based Approach. *SAFER-SIM University Transportation Center, University of Central Florida*.

Holling, C.S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*.

Zhang, Z., B. Wolshon, and P. Murray-Tuite. (2019). A conceptual framework for illustrating and assessing risk, resilience, and investment in evacuation transportation systems. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.trd.2019.08.016>

Knoop, V.L., M. Snelder, H.J. van Zuylen, and S.P. Hoodendoorn. (2012). Link-level vulnerability indicators for real-world networks. *Elsevier Ltd*.

Murray-Tuite, P.M., H.S. Mahmassani. (2004). Methodology for Determining Vulnerable Links in a Transportation Network. *Transportation Research Record*. Retrieved from <https://doi.org/10.3141/1882-11>

Taylor, M.A.P., G.M. D'Este. (2007). Transport Network Vulnerability: a Method for Diagnosis of Critical Locations in Transport Infrastructure Systems. *Critical Infrastructure. Advances in Spatial Science*. Retrieved from https://doi.org/10.1007/978-3-540-68056-7_2

Kazerani, A. and S. Winter. (2009). Modified Betweenness Centrality for Predicting Traffic Flow. *University of Melbourne, Australia*. Retrieved from <https://www.semanticscholar.org/paper/Modified-Betweenness-Centrality-for-Predicting-Flow-Kazerani-Winter/8de726360a65120da60656a1a0d5b8a2436ced21#paper-header>

Gao, S., Y. Wang, Y. Gao, and Y. Liu. (2013). Understanding Urban Traffic-Flow Characteristics: A Rethinking of Betweenness Centrality. *Environment and Planning B: Planning and Design*. Retrieved from <https://doi.org/10.1068/b38141>

Jenelius, E. (2010). Redundancy importance: Links as rerouting alternative during road network disruptions. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.proeng.2010.07.013>

Abdullah, N. and Hua, T. K. (2017). Using Ford-Fulkerson Algorithm and Max Flow-Min Cut Theorem to Minimize Traffic Congestion in Kota Kinabalu, Sabah. *Journal of Information System and Technology Management (JISTM)*. Retrieved from <http://www.jistm.com/PDF/JISTM-2017-04-06-02.pdf>

Koo, R. & Y. Yim. (1998). Commuter Response to Traffic Information on an Incident. *Transportation Research Record*. Retrieved from <http://dx.doi.org/10.3141/1621-05>

Reggiani, A., P. Nijkamp, and D. Lanzi. (2015). Transport resilience and vulnerability: The role of connectivity. *Elsevier Ltd*. Retrieved from <http://dx.doi.org/10.1016/j.tra.2014.12.0120>

Lou, Y. and L. Zhang. (2011). Defending Transportation Networks against Random and Targeted Attacks. *Transportation Research Record*. Retrieved from <https://doi.org/10.3141/2234-04>

Oswald Beiler, M., S. McNeil, and D. Ames. (2011). Identifying Resiliency Performance Measures for Megaregional Planning: Case Study of the Transportation Corridor Between Boston, Massachusetts, and Washington, D.C. *Transportation Research Record*. Retrieved from <https://doi.org/10.3141/2397-18>

Oliveira, E.L., L. d. S. Portugal, and W. Porto Jr. (2014). Determining critical links in a road network: vulnerability and congestion indicators. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.sbspro.2014.12.196>

Luathep, P., A. Sumalee, H.W. Ho, and F. Kurauchi. (2011). Large-scale road network vulnerability analysis: a sensitivity analysis based approach. *Transportation* 38. Retrieved from <https://doi.org/10.1007/s11116-011-9350-0>

Li, J. and K. Ozbay. (2012). Evaluation of Link Criticality for Day-to-Day Degradable Transportation Networks. *Transportation Research Record*. Retrieved from <https://doi.org/10.3141/2284-14>

Grubestic, T.H., T.C. Matisziw, and A.T. Murray. (2008). Comparative Approaches for Assessing Network Vulnerability. *International Regional Science Review*. Retrieved from <https://doi.org/10.1177/0160017607308679>

Tang, J., L. Zheng, C. Han, W. Yin, Y. Zhang, Y. Zou, and H. Huang. (2020). Statistical and machine-learning methods for clearance time prediction of road incidents: A methodology review. *Analytic Methods in Accident Research*. Retrieved from <https://doi.org/10.1016/j.amar.2020.100123>

Berdica, K. (2003). An introduction to road vulnerability: what has been done, is done and should be done. *Transport Policy, Volume 10*. Retrieved from [https://doi.org/10.1016/S0967-070X\(02\)00011-2](https://doi.org/10.1016/S0967-070X(02)00011-2)

Xu, X., A. Chen, and C. Yang. (2017). An Optimization Approach for Deriving Upper and Lower Bounds of Transportation Network Vulnerability under Simultaneous Disruptions of Multiple Links. *Elsevier Ltd*. Retrieved from <https://doi.org/10.1016/j.trpro.2017.05.036>

Wang Z., A.P.C. Chan, J. Yuan, B. Xia, M. Skitmore, and Q. Li. (2014). Recent Advances in Modeling the Vulnerability of Transportation Networks. *American Society of Civil Engineers*. Retrieved from [https://doi.org/10.1061/\(ASCE\)IS.1943-555X.0000232](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000232)

Rodríguez-Núñez, E. and J.C. García-Palomares. (2014). Measuring the vulnerability of public transport networks. *Elsevier Ltd*. Retrieved from <http://dx.doi.org/10.1016/j.jtrangeo.2014.01.008>

Zhou Y., J. Wang. (2018). Critical Link Analysis for Urban Transportation Systems. *IEEE Transactions on Intelligent Transportation Systems*. Retrieved from <https://doi.org/10.1109/TITS.2017.2700080>

Balijepalli, C., O. Opong. (2014). Measuring vulnerability of road network considering the extent of serviceability of critical road links in urban areas. *Institute for Transport Studies*. Retrieved from <https://doi.org/10.1016/j.jtrangeo.2014.06.025>

Ukkusuri, S.V., W.F. Yushimito. (2009). A methodology to assess the criticality of highway transportation networks. *J Transp Secur*. Retrieved from <https://doi.org/10.1007/s12198-009-0025-4>

Jenelius, E., T. Petersen, and L.G. Mattsson. (2006). Importance and exposure in road network vulnerability analysis. *KTH/Royal Institute of Technology*. Retrieved from <https://doi.org/10.1016/j.tra.2005.11.003>

Akbarzadeh, M., S. Memarmontazerin, S. Derrible, and S.F.S. Reihani. (2017). The role of travel demand and network centrality on the connectivity and resilience of an urban street system. *Transportation*. Retrieved from <https://doi.org/10.1007/s11116-017-9814-y>

Jayasinghe, A., K. Sano, and H. Nishiuchi. (2015). Explaining Traffic Flow Patterns Using Centrality Measures. *International Journal for Traffic and Transportation Engineering*. Retrieved from [http://dx.doi.org/10.7708/ijtte.2015.5\(2\).05](http://dx.doi.org/10.7708/ijtte.2015.5(2).05)

Zhao S., P. Zhao, and Y. Cui. (2017). A network centrality measure framework for analyzing urban traffic flow: A case study of Wuhan, China. *ScienceDirect*. Retrieved from <https://doi.org/10.1016/j.physa.2017.02.069>

Wang H., J.M. Hernandez, and P. Van Mieghem. (2008). Betweenness centrality in a weighted network. *Phys. Rev. E*. Retrieved from <https://doi.org/10.1103/PhysRevE.77.046105>

Dijkstra, E.W. (1959). A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik I*. Retrieved from <https://ir.cwi.nl/pub/9256/9256D.pdf>

Manley, E.J., J.D. Addison, and T. Cheng. (2015). Shortest path or anchor-based route choice: a large-scale empirical analysis of minicab routing in London. *Journal of Transport Geography*. Retrieved from <http://dx.doi.org/10.1016/j.jtrangeo.2015.01.006>

Wu, L., W. Ma, Y. Yang, and K. Wang. (2017). A competitive analysis approach for route choice with uncertain travel times and blocked nodes. *Journal of Ambient Intelligence and Humanized Computing*. Retrieved from <https://doi.org/10.1007/s12652-018-0780-9>

Shang, W.L., Y. Chen, C. Song, and W.Y. Ochieng. (2020). Robustness Analysis of Urban Road Networks from Topological and Operational Perspectives. *Mathematical Problems in Engineering*. Retrieved from <https://doi.org/10.1155/2020/5875803>

Liu, B. (2007). Uncertainty Theory. 2nd ed. *Springer*. Retrieved from https://link.springer.com/content/pdf/10.1007/978-3-540-73165-8_5.pdf

Idri, A., M. Oukarfi, A. Boumakoul, K. Zeitouni, and A. Masri. (2017). A new time-dependent shortest path algorithm for multimodal transportation network. *8th International Conference on Ambient Systems, Networks, and Technologies*. Retrieved from <https://doi.org/10.1016/j.procs.2017.05.379>

Sheffi, Y. (1985). Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods. *Prentice-Hall, Inc.*

Boyles, S.D., N.E. Lowmes, and A. Unnikrishnan. (2019). Transportation Network Analysis. Version 0.8, 2019.

Jeihani, M. and A. Ardeshiri. (2017). Transportation Network Modeling and Calibration. *Momentum Press, LLC*.

Freeman, L.C. (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*. Retrieved from <https://doi.org/10.2307/3033543>

Ford, L.R. and D.R. Fulkerson. (1956). Maximal Flow Through a Network. *Canadian Journal of Mathematics*. Retrieved from <https://doi.org/10.4153/CJM-1956-045-5>

Edmonds, J. and R.M. Karp. (1972). Theoretical Improvements in Algorithmic Efficiency for Network Flow Problems. *Journal of the ACM*. Retrieved from <https://doi.org/10.1145/321694.321699>

Jiang, Y. & J. Zhang. (2014). How Drivers Adapt to Traffic Accidents and Dynamic Travel Information: Stated Preference Survey in Japan. *Transportation Research Record*. Retrieved from <http://dx.doi.org/10.3141/2413-08>

Knoop, V.L., S.P. Hoogendoorn, and H. van Zuylen. (2010). Rerouting behaviour of travellers under exceptional traffic conditions — an empirical analysis of route choice. *Procedia Engineering*. Retrieved from <https://doi.org/10.1016/j.proeng.2010.07.012>

Zhang, Lei. (2011). Behavioral Foundation of Route Choice and Traffic Assignment. *Transportation Research Board*. Retrieved from <https://doi.org/10.3141/2254-01>

Zhang, A., K. Spansel, B. Wolshon. (2013). Megaregion Network Simulation for Evacuation Analysis. *Journal of the Transportation Research Board*. Retrieved from <https://doi.org/10.3141/2397-19>

Yu, C., X. Yang, M. Yun. (2013). Method of Searching for Critical Links in Traffic Network Based on Link Redundancy. *National Natural Science Foundation of China*. Retrieved from https://www.researchgate.net/profile/Chunhui-Yu/publication/268033899_Method_of_Searching_for_Critical_Links_in_Traffic_Network_Based_on_Link_Redundancy/links/5827390e08ae254c508314e0/Method-of-Searching-for-Critical-Links-in-Traffic-Network-Based-on-Link-Redundancy.pdf

Wardrop, J.G. (1952). Some Theoretical Aspects of Road Traffic Research. *Proceedings of the Institute of Civil Engineers*. Retrieved from <https://doi.org/10.1680/ipeds.1952.11259>

Cheng, G., C.G. Wilmot, E.J. Baker. (2008). Destination choice model for hurricane evacuation. *Presented at 87th Annual Meeting of the Transportation Research Board*.

Fu, H., C.G Wilmot, E.J. Baker. (1977). Sequential logit dynamic travel model and its transferability. *Journal of the Transportation Research Board*.

Jou, R.C., S.H. Lam, Y.H. Liu, K.H. Chen. (2005). Route switching behavior on freeways with the provision of different types of real-time traffic information. *Transportation Research Part A: Policy and Practice*.

Broumi, S., D. Nagarajan, A. Bakali, M. Talea, F. Smarandache, M. Lathamaheswari. (2019). The shortest path problem in interval valued trapezoidal and triangular neutrosophic environment. *Complex & Intelligent Systems*. Retrieved from <https://doi.org/10.1007/s40747-019-0092-5>

Makariye, N. (2017). Towards Shortest Path Computation using Dijkstra Algorithm. *JNEC, Dr. B.A.M. University*. Retrieved from <https://doi.org/10.1109/ICIOTA.2017.8073641>

Shengwu, D. and Z. Yi. (2011). Research on Method of Traffic Network Bottleneck Identification Based on Max-flow Min-cut Theorem. *2011 International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE)*.