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Enhancing Serviceability and Resiliency of Transportation Networks Based on Topological Credentials and Systematic Design Interventions

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ENHANCING SERVICEABILITY AND RESILIENCY OF TRANSPORTATION NETWORKS BASED ON TOPOLOGICAL CREDENTIALS AND SYSTEMATIC DESIGN INTERVENTIONS

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Md Ashraf Ahmed

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To: Dean John L. Volakis
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This dissertation, written by Md Ashraf Ahmed, and entitled Enhancing Serviceability and Resiliency of Transportation Networks Based on Topological Credentials and Systematic Design Interventions, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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DEDICATION

To my beloved dad, my mom, elder brother, younger brother, and the better half

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ABSTRACT OF THE DISSERTATION

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Recent advancements in network science showed that the topological credentials (i.e., rank of relative importance) of network components (such as nodes and links), carry significant implications as it is critical to know which components contribute the most to the overall network performance. For transportation networks, critical components (roads, bridges) may become inaccessible for adjacent traffic due to day-to-day congestion or external disruptions (i.e., man-made or natural hazards) that significantly reduce the level of service. Hence, topological credentials of critical network components based on their connectivity need to be assessed to enhance the serviceability, i.e., improved travel time experience as well as the ability to recover from sudden disruptions. Although the literature on network science and transportation systems' resilience has recently advanced, the empirical literature does not provide enough guidance on systematic applications of topological credentials to infer novel, more efficient strategies for transportation network resilience and serviceability.

The goal of the dissertation is to enhance the serviceability and resiliency of transportation networks based on the topological credentials of network components as well as systematic design interventions made on critical components. To achieve this goal, this dissertation emphasized coordinated and extensive network experiments conducted at different geographic scales (i.e., city, county, and state) by using real road network data from several locations, including Miami-Dade County, Sioux Falls, Boise, among others. Results indicate that network credentials change significantly when different attributes (i.e., vehicular traffic) are introduced to the network topology. Such credentials also contribute towards generating recovery schemes in the aftermath of any network disruptions. In addition, microscopic traffic simulations indicate that design interventions, such as increased number of travel lanes on critical links, help achieve better serviceability rather than intervening on less critical congested links. The methodologies and findings of the dissertation can help traffic managers and practitioners decide on recovery strategies and design interventions efficiently to ensure more serviceable and resilient transportation networks.

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INTRODUCTION

1.1 Background

A network consists of two basic components: nodes and links (Newman 2002), and the connectivity of these nodes by the links can be directional as well as weighted (Newman 2004). Real-world infrastructure systems often take the form of networks (Newman 2003), such as transportation networks. Moreover, resilience is a metric that determines the ability of a system to withstand (robustness) an unusual and extreme intervention and to recover (rapidity) efficiently from the damage induced by such perturbation (Timmerman 1981). Network resilience is explained by removing random nodes in the network (Figure ***1***) as the level of resilience to such node removal varies across networks depending on the network topology (Newman 2003). Networks in which most of the nodes have low degree (number of connections with other nodes) have less disruption since these nodes lie on few paths between others, whereas removal of high degree nodes in a large real network can result in major disruption (Albert 2000).

Many new network concepts, properties and measures have been developed by applying experiments on large-scale real networks (Barrat et al. 2008). Some of these properties, such as node and link centrality, small world and scale-free property are common across many real networks (Albert and Barabási 2002). Centrality defines a critical node which lies mostly on the shortest path of other pairs of nodes as well as closeness, on average, to other nodes. Small-world property refers to the existence of relatively short paths (at most six steps) between any pair of nodes in most networks despite their large size (Milgram 1967; Travers and Milgram 1969; Watts and Strogatz 1998). The small-world effect has significant implications in explaining dynamics of processes occurring on real networks (Newman 2003). The degree of a node is the number of direct links to other nodes in a graph. The degree distribution in real networks is insignificantly different from the Poisson distribution; in fact, real networks exhibit a power law or scale-free degree distribution (Barabási and Albert 1999). In addition, many real networks also exhibit significant correlations in terms of node degrees or attributes. This scale-free property validates the existence of hubs, or a few nodes that are highly connected to other nodes in the network. The presence of large hubs results in a degree distribution with long tail (highly right-skewed), indicating the presence of nodes with a much higher degree than most other nodes.

Recently the concept of resilience is becoming more prevalent, and it is defined by four metrics: robustness, rapidity, redundancy and resourcefulness (Bruneau et al. 2003). Madni et al. stated that any infrastructure (i.e., transportation) network that can anticipate extreme events, rebound from disruptions, and evolve by adaptation are all examples of resilience engineering (Madni and Jackson 2009). It is critical to know which components are most significant to the overall network's success, and therefore vulnerable to disruptions when designing and managing infrastructure (i.e., transportation) networks. Even though reliability engineering is extensively studied, few studies have been found to assess the components of vulnerability in the context of the overall resilience of transportation networks (Barker et al. 2013; Baroud et al. 2014; Wan et al. 2018). Other studies include accessibility metrics, performance-based resilience metrics and socio-economic resilience metrics (Sun 2018).

Despite the advances in resilience engineering, there are still fundamental obstacles to a holistic assessment that enhances the resiliency and serviceability of the transportation networks. Existing literature on network science and transportation system resiliency emerged recently, and the necessity of developing an effective framework for measuring transportation network resiliency as well as application of design interventions systematically to improve network serviceability is lacking.

1.2 Problem Statement

The serviceability of transportation network can be interrupted by any external event (natural and man-made). Due to this, the system serviceability decreases significantly (less robustness) as well as takes longer to recover (rapidity) from the disruption to an adequate level of service. Due to external shocks, some critical intersections (nodes) and roadways (links) may become inaccessible for neighboring traffic; they may undergo maintenance activities resulting in significant increases in travel time and delay, hence reducing the serviceability. For faster recovery of the network serviceability, systematic identification of the critical network components (intersections and roadways) and implementation of design interventions to prioritize restoration is essential.

1.3 Research Objective

The aim of this research is to understand how complex network metrics can enhance transportation network resiliency and develop a systematic approach to improve the network serviceability. This research analyzed road and bridge networks to achieve this goal. The specific objectives of the research are stated as following:

- Develop a systematic strategy for identifying the critical components (i.e., roads, bridges) of transportation network.

- Unify network science principles and infrastructure resiliency to achieve the network resiliency at different scales of real networks (e.g., transportation network) through data-driven methods.
- Evaluate a methodology to recover (resilience) from disruptions by systematic restoration of critical components (i.e., roads, bridges) effectively.
- Develop an efficient approach that applies design interventions on critical components (i.e., roads) to improve transportation network serviceability.

1.4 Conceptual Framework

A conceptual framework is developed to depict the proposed methodology for enhancing transportation network resiliency and serviceability. Identification of the critical components (i.e., intersections and roadways) of transportation networks can help ensure effective recovery from any disruption to enhance resiliency, implementing design interventions on critical components for improving the serviceability. In Figure 1, the original network shows a simple road networked system consisting of 7 intersections and 12 roadways (directed). When a critical intersection of the network became inaccessible due to any disruption, the serviceability of the networked system reduces significantly.

The disrupted network shows the removal of one critical intersection which causes the removal of four connected roadways from the network. The resiliency is depicted by the resilience triangle, which is defined by the robustness (i.e., serviceability) and rapidity (how fast a network can recover) of a network, where the area of the triangle represents the loss of resilience rather than resilience itself.

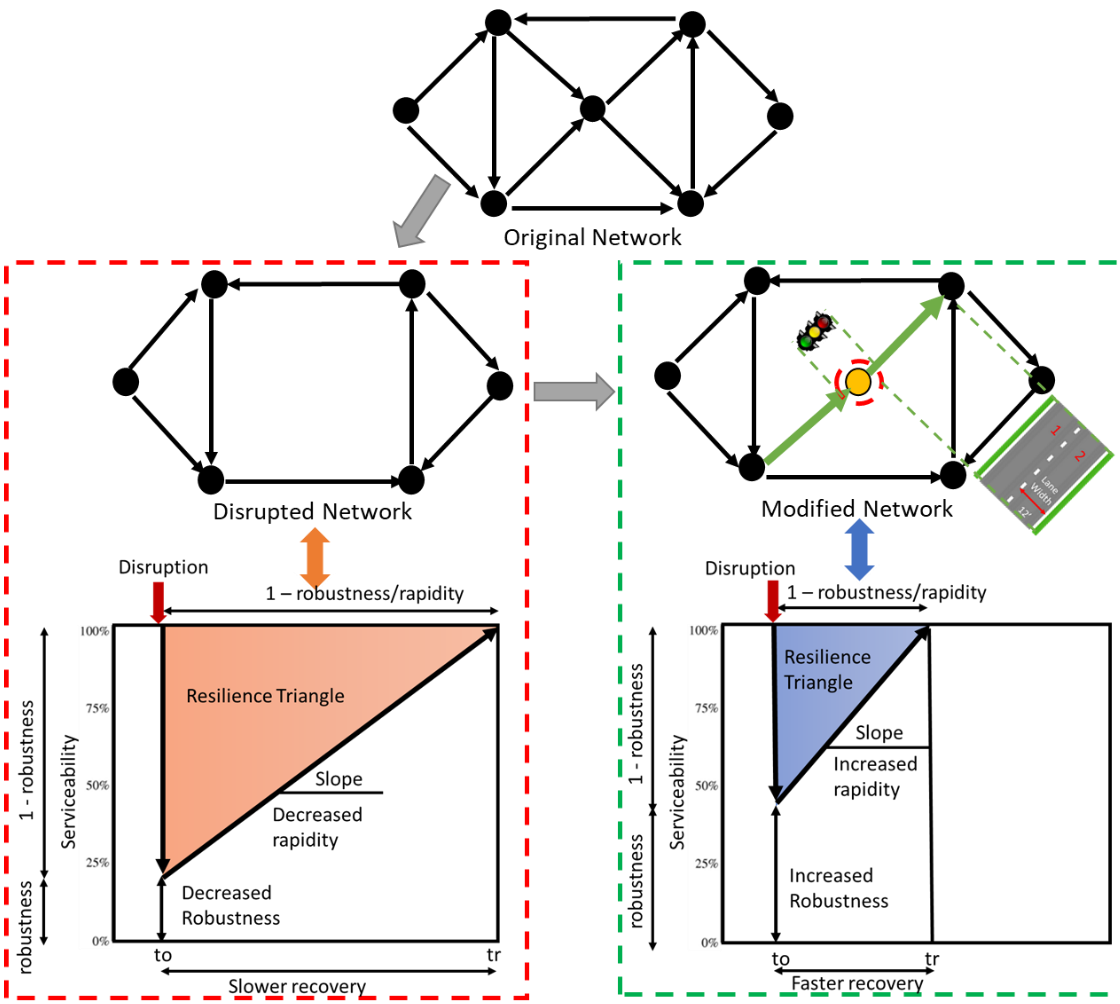


Figure 1: Conceptual Framework of Enhancing Network Resiliency and Serviceability

The corresponding resilience triangle shows the systems' serviceability decreased to around 20% from full serviceability due to removal of critical intersection and roadways, which results in a longer recovery time for the disrupted network.

In case of the modified network, the most critical intersection and two roadways are restored and incorporated with design interventions. These interventions can be applied to both intersections (i.e., traffic signal timing optimization) and roadways (i.e., increasing number of lanes, lane width). Due to the removal of two less critical roadways, the network serviceability reduces to around 50%, which is much less than the disrupted network. Here, restoring and implementing design interventions on critical intersections and roadways ensures a better serviceability of the network. The area of the resilience triangle (loss of resilience) is also smaller than the disrupted network, ensuring a faster recovery of the networked system.

1.5 Dissertation Organization

The dissertation consists of a total of five chapters. Chapter 1 includes introduction, problem statement, objective, and the conceptual framework of the research work. A comprehensive literature review on serviceability of transportation network, resiliency of transportation network, network science principles, and application of network science in transportation system are conducted in Chapter 2 to identify the knowledge gaps in the literature. Chapter 3 proposes a methodology to enhance the resiliency of transportation (i.e., road-bridge) networks. Chapter 4 explains a systematic approach to improve transportation network serviceability by implementing design interventions on critical infrastructure components (roads). Chapter 5 summarizes the findings and contribution of the dissertation, provides recommendations for future studies, and listed the limitations of the research.

CHAPTER 2

LITERATURE REVIEW

2.1 Serviceability of Transportation Networks

Transportation networks forms the mainstay of the economy and requires huge number of annual investments which are mainly for regular maintenance, restoration, and replacement of the assets. Infrastructure aging, increased frequency, the intensity of severe weather, and additional traffic loads are the main factors for excess expenditure. Several factors play vital role in advancing modern building strategies, planning methods and management policies. These include the importance of the bridge network for transport and economic growth, the substantial investments in maintenance/replacement and the effects of their closures on the socio-spatial stability of society. Due to the growing budgetary constraints, the necessity of cost-effective prioritization for repairing and replacing the deteriorating bridges is the biggest challenge faced by the transportation asset managers. The decision-making processes are exacerbated by the indirect costs (e.g., traffic delay) due to the road closure times during these activities (Alipour et al. 2018b).

Alice et al. showed that the major aspects impacting the timelines for construction projects are the effects of the closures and the socio- economic aspects of the community by interviewing a few states that already practiced innovative construction methods at various levels. Therefore, the value of indirect costs is acknowledged in most entities, with the exception that some do not have a quantitative language to compensate for in the final decisions of the stakeholders. Based on the districts' qualitative data and public discussions, most of the state level decisions have made (Alipour and Shane 2018a). Researchers proposed a programming model incorporating a mixed-integer method that provides a balanced portfolio of bridge construction techniques through bridge priority processes at network-level. A project level program is carried out to optimize the option of accelerated construction methods, while a network level framework is used to identify rapid replacement bridges based on their criticality to the network. The costs involved with replacement method include direct costs for actual bridge replacement and indirect costs incurred by network users during the repair time to illustrate the effects of various construction methods (Alipour et al. 2018b).

Saberi et al. explores the effects of adaptive driving in the simulated network model of the Chicago metropolitan area on network capacity and traffic instability. The findings show that the general trend for network ability often increases as the number of adaptive drivers' increases. Adaptive driving is also found to increase average network traffic, but does not inherently boost the performance of the network (Saberi et al. 2015). The DTA model, which involves the calibration of a broad range of requirements and supply input parameters was applied by Shafiei et al. In this study, a data-intensive system for the deployment, calibration and validation of Melbourne, Australia as a large-scale congested network of a simulation-based DTA model is presented. The authors recommend a technique based on machine learning to identify and calibrate simple diagrams of traffic flow. Results of validation indicate that the calibrated DTA model replicates traffic trends throughout the network successfully (Shafiei et al. 2018).

Transportation system is examined in literature to capture the influence of traffic assignment, whereas user equilibrium ensures better safety and adaptability, besides system optimum yields better mobility and recovery (Murray-Tuite 2006). Besides, real road network is developed and experimented by the researchers as well as the developers of simulation software's to understand the dynamics of traffic flow, travel demand (Zhao et al. 2010) and the walkability of pedestrians (Speck 2014). These networks have also tested for disruption due to traffic incident (Hurlburt et al. 2019) as well as for transportation system criticality (Abdel-Rahim et al. 2006).

The travel time reliability used as a descriptor of network efficiency is of increasing interest to both the traveling public and traffic managers and policy makers. Mahmassani et al. clarified the nature of the fundamental diagram of the network at the scale of the urban network. Analytically, robust interactions between travel time variability and network density and flow rate were derived in this study (Mahmassani et al. 2013). Zockaie et al. demonstrates the presence of hysteresis for unloading reloading when a network is subject to consecutive loading and unloading cycles. The findings suggest that, as previously assumed, the linear relationship between average network flow and trip completion rate does not always hold. The average traffic flow, but not necessarily the network output, can artificially be improved by regular route changing by adaptive drivers (Zockaie et al. 2014).

2.2 Resiliency of Transportation Networks

To support resilience planning for roadway networks, Zhang et al. introduced a new stage-wise decision framework concerning mitigation at pre-disaster scenario (Stage I), emergency response at post-disaster (Stage II) and long-term recovery (Stage III). These decision measures are established to quantify the network performance in terms of robustness, redundancy and recovery, based on a derivation of the independent routes of a road network (Zhang 2018). Machado et al explains social resistance which depends on the resilience of the lifeline infrastructure and the execution of the disaster-related functions of local governments. The research condenses the metrics used to assess the resilience of the transportation system and a categorization of the assessment approaches at three levels of analysis (the asset, network, and systems levels) (Machado-León 2017).

Sun et al states that the transportation infrastructure plays an important role in ensuring the well-being of its citizenry and for supporting the national economy. There is an increasing number of studies focusing on the resilience analysis of the transportation infrastructure to support planning and design and to optimize emergency management and restoration schedules. Extreme events (including both natural hazards and man-made disasters) have caused terrible physical damages to the transportation infrastructure, long-term socioeconomic impacts, and psychological damages. This study covers serviceability metrics, serviceability-based resilience metrics and socio-economic resilience metrics. The study also revealed that there are still fundamental challenges to comprehensively evaluate the resilience of the transportation infrastructure, especially due to two main sources of complexity: uncertainties and interdependencies. Besides, the validations of resilience assessments are limited due to the general scarcity of data, which may hinder the practical applications (Sun 2018).

To understand the network-wide consequences of disruptive occurrences, Twumasi et al. explained the negative impacts on regional network infrastructure, and the identification of considerably affected areas is significant to communicate the need of constructing the robust infrastructure as a key area in assessing transport network robustness at local level (Twumasi-Boakye 2018).

To improve the recovery process after any extreme event, Zhang et al. developed a new resilience-based framework for road transport network with bridges. The approach integrates road system topography, reliability, flow and volume of traffic, deterioration level and accessible resources into the design of the recovery strategy of the network stochastic processes after disaster. Two measures were developed to calculate network recovery speed and efficiency: TRT (total recovery time) and SRT (skew of the recovery trajectory). The timeline needed to restore the system to its pre-disaster functionality is named as TRT. Besides, the SRT is a measure uniquely established by the researchers to observe the criterions of the recovery path that are linked to the effectiveness for the approaches taken for restoration (Zhang 2017).

Frangopol et al. stated that the bridges are the most vulnerable to earthquake damage in a transportation network; thus, the anticipated solution was centered on bridge restoration interventions. The study examined the concept of "resilience" and proposed its application as a criterion for optimizing the rehabilitation of an earthquake prone transport network (Frangopol 2011). Bocchini et al. identifies the most important areas in which the idea of resilience is applied to engineering practice in the advancement of instruments for assisted decision-making in disaster management. The proposed method for optimal disaster management is recommended, which provides bridge restore sequences that optimize network durability and minimize the time needed to connect critical sites (Bocchini 2013). Karamlou et al. developed a unique approach to schedule the renovation of the deteriorated bridges by developing an algorithm which provided a practical restoration plan during any disruption; based on calculations other than applying technical experience. (Karamlou 2014).

Banerjee et al. provided an organized and wide-ranging review on bridge and bridge network resilience assessment under single hazard and multi-hazard conditions. Resilience assessment for engineered systems in recent years has attracted considerable attention from the engineering community. It has resulted in a large body of literature that focuses on relevant areas of resilience. Authors mentioned not that much work has yet been done on multi-hazard bridge resilience, relevant aspects are discussed, including combinations of multiple hazards for bridge performance assessment, loss assessment methods, and post-event recovery approaches. In addition, maintenance is a key component when a life-cycle framework evaluates resilience. Accessible maintenance plans and strategies are discussed as well as their likely applications for bridges and bridge networks. The article ends with a debate on the need for more work in the focus area and the challenges associated with it (Banerjee 2019).

Domaneschi et al. stated that structural management systems can make a significant contribution to reducing the impact of extreme events in areas affected by the earthquake, thus improving structural resilience. In addition, as structural conditions change due to local failures, the inherent advantage of some control systems, which can adjust to various loading rates, can be exploited. This happens by changing the control system's working parameters in real time or over the period between two seismic events, even if very short. This research deals with the durability of cable-stayed bridge seismic control solutions through a case study defined by a standard literature bridge control benchmark. Authors introduced a technique to restore the optimum bridge configuration after a damaging incident. Emphasis is placed on the time interval between the occurrence of damage and the recovery, which is the essential aspect of the resilient actions. Ultimately, in the sense of multiple hazards, the development of a robustness index and general procedures indicating how to measure durability for the cable-stayed bridge control system is discussed (Domaneschi 2015).

Frangopol et al. discussed about a systematic method to optimize the reconstruction works related to the bridges of an earthquake damaged transportation network. The goals were to optimize the efficiency of the network, reduce the timeline needed to achieve a certain level of efficiency, and reduce the overall expenditure of restoration activities (Frangopol 2012). Apostolopoulou et al. refers to traditional inheritance properties that have suffered huge damage, requiring widespread restoration with quality materials for sustainable monument conservation (Apostolopoulou 2019).

Setunge et al. stated that the road networks and critical road systems such as bridges, culverts and floodways play a vital role in increasing the risk of the area being served before, during and after extreme events. The research presented a detailed analysis of the Lockyer Valley region of Australia's case study of 2013 floods to identify critical failure mechanisms of road bridge structures exposed to flood events. 43 out of 46 bridges in the region have been damaged because of the 2013 flood. Major bridge structure failure mechanisms are described as scouring of piers and abutments, damage to bridge decks due to impact of urban debris, and severe damage to bridge approach ramps. A methodology is proposed for vulnerability modeling of bridges for an extreme event, consisting of a combination of the definition of fault tree system and harm index (Setunge 2014).

Karamlou et al. presented a new scheduling methodology to restore affected bridges. The scenario is articulated as a multi-objective, Genetic Algorithms computational optimization that reduces the time for connecting the selected critical locations and increases the responsiveness of the transport network (Karamlou 2014). Tao et al.

described that bridge quality can deteriorate due to aging, traffic-induced fatigue, and environmental corrosion throughout their lifetime. Structural instability in earthquake-prone areas raises bridge seismic vulnerability, which means an increase in potential future economic and social losses. Therefore, determining the optimum maintenance strategies regarding bridge deterioration is of critical importance (Tao 2019).

Pritchard (2013) identified a range of issues that have been encountered because of the floods and cyclone events from 2011 to 2012 in Queensland, Australia. These included timber bridge destructions, pier settlement, abutment scouring, and the loss of road approaches to bridges. The AS 5100 Bridge Design Code is assumed to have been written primarily for traditional rural applications. In addition, this paper discusses the specific loads to which urban bridges are subject, including floating debris such as shipping containers, vehicles, and rivercraft (e.g., 300 t vessels) to be included in future revisions of AS 5100. Bridge design codes were suggested to consider the context and location of bridges for accessibility and usability after catastrophe in the future. It is recommended that such training be considered and implemented in accordance with suggested changes to the AS 5100 Bridge Design Code for new bridges and remedial works (Pritchard 2013).

2.3 Network Science

2.3.1 Small-world Property

This feature refers to the presence of relatively short pathways between any two nodes in most networks, regardless of their size. This characteristic can be found in many real-world networks (Milgram 1967; Travers and Milgram 1969; Watts and Strogatz 1998). The small-world effect has fundamental significance for explaining the dynamics of real-world systems. As most real-world networks have short average path lengths, the small-world property implies that distributing information or ideas via a network will be faster (Newman 2003). Eccentricity, radius, and diameter are three crucial metrics that explain this feature. While a node's eccentricity is the maximum distance (number of steps or hops) from this to all other nodes in a graph, the radius and diameter are the minimum and maximum eccentricity observed among all nodes, respectively.

2.3.2 Scale-free Property

A node's degree (k) is the number of direct connections it has to other nodes in a graph. The Poisson distribution, which is generally used in the modeling of random graphs, is notably different from the degree distribution P(k) in real networks (probability that a randomly selected node has degree k). In fact, real networks follow a power law (or scale-free) degree distribution with larger triangle densities (Barabási and Albert 1999).

Furthermore, in terms of node degrees or properties, many real networks show substantial correlations. The presence of hubs, or a few nodes that are highly connected to other nodes in the network, is validated by this scale-free property. The presence of big hubs causes a long tail (very right-skewed) degree distribution, suggesting the presence of nodes with a substantially higher degree than many other nodes. For an undirected network, the degree distribution $P_{degree}(k)$ can be written as follows:

$$P_{degree}(k) \propto \; k^{-\gamma} \tag{1}$$

where γ is an exponent and $P_{degree}(k)$ decays slowly as the degree k increases. Besides, the probability of obtaining very high degree nodes also increase. The networks which follow power-law distributions are known as scale-free networks (Albert and Barabási 2002) that maintains the similar operational form (power laws) at all scales. The power law $P_{degree}(k)$ remains unchanged (other than a multiplicative factor) when rescaling the independent variable k by satisfying:

$$P_{degree}(xk) = \; x^{-\gamma} \, P_{degree}(k) \tag{2}$$

Power law networks are characterized by hubs, that are orders of magnitude greater in degree than many other nodes.

2.3.3 Network Resilience

Resilience is the ability of an infrastructure to withstand (robustness) external shocks or perturbations and to recover (rapidity) from such perturbations. The function refers to network resilience due to the removal of random nodes in the network. The degree of resilience to such vertex elimination varies across the network depending on network topology. Networks with least connected nodes experience less disturbance because these nodes lie on few pathways between others, while removing highly connected nodes from a huge real network may lead to serious disturbances. If nodes are removed from a network, the usual length of those paths will be increased and the communication between networking agents will be harder (Newman 2003).

2.3.4 Node Degree

The degree of a node is the number of direct connections or links to the other nodes (deg_i) in a graph. Degree can be explained in two sub-definitions, in-degree, and out-degree. In-degree is the number of links directing into the nodes (in_deg_i) and out-degree is the number of links directing out of the nodes (out_deg_i) .

2.3.5 Network Centralities

Betweenness centrality

The summation of the portion of all-pairs shortest path that traverse to node i defined as the Betweenness centrality (BC_i) of node i:

$$BC_i = \sum_{x,y \in V} \frac{\theta_{(x,y \mid i)}}{\theta_{(x,y)}} \tag{3}$$

where, V= a set of nodes (where $x \neq y$) in G, $\theta_{(x,y)}$= number of shortest (x, y) paths, and $\theta_{(x,y \mid i)}$= number of paths that traverse to several nodes i other than (x, y) (Brandes 2001; Brandes 2008; Brandes and Pich 2007).

Closeness centrality

The closeness centrality (CC_i) in the graph G of node i is the inverse of the summation of the spaces between shortest paths from node i to all other $(n-1)$ nodes:

$$CC_i = \frac{n-1}{\sum_{j=1}^{n-1} \theta_{(j,i)}} \tag{4}$$

In graph G, $\theta_{(j,i)}$= spaces between shortest paths from node j to node i ($j \neq i$) and n= number of entire nodes. Closeness centrality is standardized by the summation of least possible spaces of $(n-1)$ nodes meanwhile the summation of the spaces relies on the number of nodes in the graph network. Higher centrality is defined by the higher values of closeness (Freeman 1978).

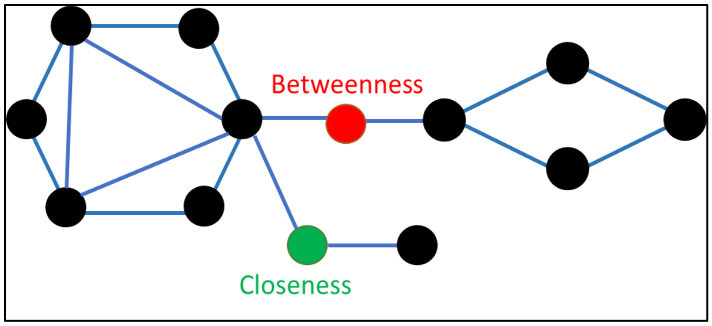


Figure 2: Networked Representation of Betweenness and Closeness Centrality

Edge betweenness centrality

Edge betweenness centrality measures the betweenness centrality for links or edges. Betweenness centrality of a link *e* is the summation of the portion of entire duos shortest paths that traverse to *e*:

$$C_B\,(e) = \sum_{s,t\,\in V} \frac{\sigma\,(s,t\,|e)}{\sigma\,(s,t)} \tag{5}$$

where *V*= a set of nodes (where $s \neq t$), σ *(s, t)*= number of shortest *(s, t)*-paths, and σ *(s, t |e)*= number of paths which traverse to link *e* (Brandes 2008; M. E. J. Newman 2005).

2.4 Application of Network Science in Transportation System

Recent emergence of network science has contributed to the literature of transportation system resiliency significantly. Topological credentials (i.e., degree, centrality) of networks carry considerable implications to identify the critical components (i.e., roads, bridges) of transportation systems. Networks in which most of the nodes have low degree (number of connections with other nodes) and centrality (topological position of a node in a network) (Derrible and Kennedy 2011) have less disruption since these nodes lie on few paths between others (Derrible 2012), whereas significant reduction in serviceability due to the disturbance of high degree and central nodes in a large real network is observed (Albert 2000). It is also hypothesized that the topological credentials of network significantly affect the resiliency of transportation system (Zhang et al. 2015). Besides, the resiliency of an undirected road network is quantified by implementing graph theory under both random and rank-ordering node removal scenarios (Rouhana and Jawad 2020).

The degree distribution in real networks is significantly different from the Poisson distribution, typically assumed in the modeling of random graphs. In fact, real networks exhibit a power law or scale-free degree distribution characterized by higher densities of triangles (Barabási and Albert 1999). In addition, many real networks also exhibit significant correlations in terms of node degrees or attributes. Network metrics are also used to identify the influential cities and bridges of a road network where cities and bridges were considered as nodes during network analysis (Mohmand and Wang 2013; Rokneddin et al. 2013).

The impact of disruptions on traffic conditions is quantified by applying dynamic weights and a network metric, degree centrality. The suggested methodology also uses temporal and weighted graphs to compute multiple metrics (e.g., heterogeneity, density, and symmetry) from complex networks theory (Henry et al. 2021). Besides, the importance of both the spatial and temporal dimensions (betweenness centrality and global efficiency) in assessing transportation system criticality, emphasizing the need of examining topological features and traffic dynamics together in the research of transport network. The consequences of area-wide interruptions have also been shown to differ from single-link failures (Henry et al. 2019; Henry et al. 2021).

Saberi et al. described that the urban travel demand can be viewed as a weighted directional graph on a large scale. Study investigated statistical properties of the dynamic weighted network of urban trips of the selected cities. In Chicago and Melbourne, authors compared selected network characteristics of travel demand trends (Saberi et al. 2017). Another research discussed a gap regarding the presence of exit flow and recovery time in the literature. Authors also demonstrated that complex urban networks with different route choices appear at lower jam densities than the theoretical average jam density of the network. This study explored how urban street network mobility could be increased by controlling the accumulation of vehicles and redistributing network traffic (Mahmassani et al. 2013). However, with the advent of dynamic network theory in the last decade, research on transportation system has advanced dramatically. The majority of highways, roads, and railways are built out in a network pattern, with connection flows, travel time, and geographical distance acting as weights (Lin and Ban 2013).

Network scientists extensively studied application of graph theory and network science to design transportation network. Existing research has demonstrated that scale-free networks are highly resilient to random failure, but vulnerable to targeted attacks (Bao et al. 2009). Derrible et al. applied the idea of scale-free and small-worlds networks for transit networks (Derrible and Kennedy 2011). Betweenness centrality is found consistent and evenly distributed with respect to other topological credentials of complex network for 28 metro system worldwide. The metro stations with higher betweenness centrality are identified to redistribute passengers to make stations less crowded (Derrible 2012). Besides, robustness of road network is studied due to flood occurrence. Betweenness centrality (robustness indicator) is observed to be redistributed after extreme flooding conditions for two cities (NYC and Chicago). Robustness of the road network is measured in terms of the loss of nodes (i.e., intersections), links (i.e., road segments) and the total length of affected roadways. Robustness also depends on many other factors such as structure of network, geography, network size and the vulnerability to disaster (Derrible and Kennedy 2010; Kermanshah and Derrible 2017).

Ukkusuri et al. addressed the issue related to robust traffic network design problem for uncertain demand. The researchers proposed a novel methodology to design robust network problem using genetic algorithm as well as defined robustness by minimizing the total system travel time (Ukkusuri et al. 2007). A new methodology is proposed by Ukkhusuri et al. to examine the criticality of transportation network. The proposed criticality measure considered travel time as a performance metric. The application of the proposed methodology on theoretical network (Sioux Falls) and real transportation network (Manhattan) showed effectiveness to identify crucial links of transportation network (Ukkusuri and Yushimito 2009). A dual-vertex split recovery model is proposed by Zhan et al. to model the functional failure and recoveries of congested road network (Zhan et al. 2017). Dual representation of network is also applied for water distribution network and drainage network where pipes are considered as nodes and intersections as links. Dual nodes with higher degrees construct the backbone of the network (Zischg et al. 2017).

2.5 Synthesis of Existing Literature and the Knowledge Gaps

Existing literature on enhancing serviceability and resiliency of transportation networks provides expressive insights for both response and recovery phases of external event. A network level framework is used to identify rapid replacement of transportation network components (i.e., roads, bridges) based on their criticality to the network. The costs involved with replacement method include direct costs for actual roads and bridges replacement and indirect costs incurred by network users during the repair time. Moreover, single hazard and multi-hazard resiliency assessments for highway network highlighted the importance of the maintenance of network components. A robustness index and general procedures are developed to measure durability of transportation networks during an earthquake event. Markovian framework is proposed for optimum maintenance of deteriorating roads and bridges, as well as a multi-criteria intervention optimization process is formulated for restoration of transportation networks in earthquake-prone areas. Besides, an evaluation of new building materials for the restoration of transportation network components is identified. A framework to model the vulnerability of transportation network for extreme flood event is proposed, which includes the consequences for flood and cyclone events, timber bridge destruction, pier settlement, abutment scouring, and the loss of road approaches to bridges. A new scheduling methodology is introduced to restore damaged roads and bridges to optimize the restoration sequence to enhance resilient transportation networks. Two metrics are proposed to calculate network recovery speed and efficiency: total recovery time (TRT) and the skew of the recovery trajectory (SRT). These important metrics can influence the planning, evaluation, and rebuilding guidelines of transportation network.

The advancement of network science in incorporating transportation system resiliency and serviceability have unfolded an emerging, multidisciplinary field of research. The empirical studies have highlighted the application of network science (i.e., topological credentials) for various types of transportation systems (i.e., weighted/unweighted graph) by considering different factors (i.e., travel time, number of trips as weight). Few studies have applied topological credentials of networks at aggregated level (i.e., cities as nodes) and developed their own algorithms as well as metrics to quantify the resiliency and serviceability of transportation network. Even though these studies helped explaining different ways of enhancing transportation network resiliency and serviceability, a thorough understanding of an effective methodology to achieve transportation network resiliency and serviceability is required. A review of the existing literature concerning to the impacts of topological credentials on transportation network resiliency and serviceability shows three major gaps in the existing knowledge.

- The existing approaches do not provide enough guidance on systematic applications of topological credentials for effective recovery from disruptions to enhance transportation network resiliency.
- The empirical literature did not consider the systematic implementation of design interventions to improve serviceability based on the topological credentials of transportation networks.
- Application of topological credentials is limited to such transportation networks (i.e., unweighted network, origin-destination demand for weighted network) which does not represent the real-world scenarios for enhancing resiliency and serviceability. A need for exploring real transportation networks with practical factors (i.e., traffic volume for weighted network) is required.

CHAPTER 3

ENHANCING TRANSPORTATION NETWORK RESILIENCY

3.1 Background

Infrastructure system is defined as the basic physical and organizational structures and facilities needed for the operation of society. Civil infrastructure systems such as transportation (roads with bridges), water supply, sewerage, power, and telecommunications provide vital services to contemporary society. Specifically, transportation infrastructure system is comprised by tangible and intangible components that develop ubiquitous, interdependent, and complex socio-economic and technical networks. Resilience is a metric that determines the ability of a system to withstand an unusual and extreme intervention and to recover efficiently from the damage induced by such perturbation. The concept of resilience is becoming more prevalent and is defined by four metrics: robustness, rapidity, redundancy and resourcefulness (Bruneau et al. 2003). Moreover, the topology of infrastructure network consists of two basic components: nodes and links. The connectivity of the nodes by the links can be directional as well as weighted (e.g., traffic volume). Topological credentials of transportation system can be quantified at system level by applying network metrics (e.g., degree, centrality) to identify the most critical and vulnerable components (e.g., bridges) of the network.

Identifying the vulnerable sections and cascading effects in the transportation (road-bridge) network system can be quite challenging. Potential failure in a transportation (i.e., roads with bridges) network system is often overlooked, but the consequences can be catastrophic as it can adversely affect the mobility of people. Therefore, addressing the vulnerabilities is very complicated in large cities. While there have been studies that discussed the necessity of developing framework for measuring resilience (Ahmed et al. 2020; Roy et al. 2020), a systematic approach to improving resiliency considering topological credentials of infrastructure components (i.e., bridges) is lacking. With growing attention to risk-based inspection and maintenance of infrastructure, an accurate knowledge of the vulnerabilities and importance, as well as consideration of interrelation among bridges in a network, becomes crucial.

The vulnerability and resilience of the Florida road-bridge network are analyzed in this study based on network science principles and graph theory. For example, the bridge connectivity is treated as a network to assess the interdependence between the connectivity of the system components and their functional behavior (Newman 2003). In accordance with the network science literature, these network links and nodes can be analyzed with respect to the resilience metrics to determine the critical components of a bridge network system that are more susceptible to external shocks. Once the vulnerabilities have been identified, priorities are set to improve the different vulnerable sections of the bridge network system. Furthermore, a plan is developed here to improve the resiliency of all the different components of the bridge network systems. A preliminary literature review is provided here to motivate how network science principles can be applied to the study of bridge network resilience.

The goal of this study is to develop an effective framework for enhancing the resiliency of transportation networks. The bridge network in Florida (United States) is used as a case study for this research. This study is focused on coordinated and extensive network experiments at different geographic scales to apply complex network science principles on the study of Florida road network resilience. The research has used geospatial modeling along with Florida bridge and road network data to run network experiments and prioritize certain bridges based on their network credentials. Essentially, the methodology has attempted to establish relationships between bridge topography with their functional behavior. The specific objectives of the study include-

- Develop systematic strategy for identifying the topological credentials (i.e., centrality) of infrastructure components (i.e., roads, bridges) of transportation system.
- Evaluate a methodology to recover (resilience) from disruptions by systematic restoration (i.e., recovery scheme) of infrastructure components (i.e., roads, bridges) effectively.
- Examine the scaling effects of the network by developing recovery schemes at different scales.

To achieve the goal and objectives of the study, the following research questions are explored.

- Can sequencing of topological credentials enhance the system serviceability of road-bridge infrastructure system?
- Do the topological credentials of road-bridge infrastructure sustain or vary at different scales of the network?
- How can implementing the systemic identification of topological credentials practically improve the resiliency of road-bridge network?

The research provides new insights into transportation network resilience based on the topography of vulnerable bridges and monitoring system-wide cascading effects. By applying network science principles, topological credentials (i.e., centrality) of bridges are identified for both unweighted (considering only network connectivity) and weighted (considering both traffic volume with network connectivity) network. The outcome of the study can prompt policy makers to emphasize the maintenance and retrofitting of those bridges, which can enhance the effective recovery of bridges after an extreme event, hence ensuring resiliency. Similar methods can be applied to new construction activities by prioritizing the construction sites. The study has developed an approach that states, municipalities, and other transportation authorities can use to select the proper actions to recover disrupted bridges by implementing new methods and risk-based strategies.

3.2 Methodology

To identify the most critical bridges of the road network, Closeness Centrality (node property) and Edge Betweenness Centrality (link property) are considered as the network parameters. Besides, traffic volume, i.e., Average Annual Daily Traffic (AADT) which is calculated by counting the total volume of vehicles of a road for a year divided by 365 days, is also considered as a network attribute (i.e., weight) for the network analyses. The road shape file is converted to network readable file by using NetworkX, a library of python programming language. NetworkX is developed for the formation, management, and training of the configuration, dynamics, and purposes of multifaceted networks (Mortula et al. 2020; NetworkX 2019). The key steps involved in network analysis of shape files are summarized and in Figure 3 below:

(1) At first, python programming language is used to convert the road shape file to network readable file for network analysis; (2) NetworkX library in python language is used to convert the shape files; (3) NetworkX library converts the geolocation information of the road-bridge network shapefile to a network graph, which contains the starting and end

points information of roads by specific labelling; (4) This network graph is internally created within the python code; it is not necessary to import the network graph as NetworkX library can directly analyze the graph; (5) Then, network analysis is performed on the road shape files for different network parameters; and (6) Finally, the output files resulted from the network analyses of road shape files; then, bridge shape files were mapped according to the common road names to identify the influential bridges.

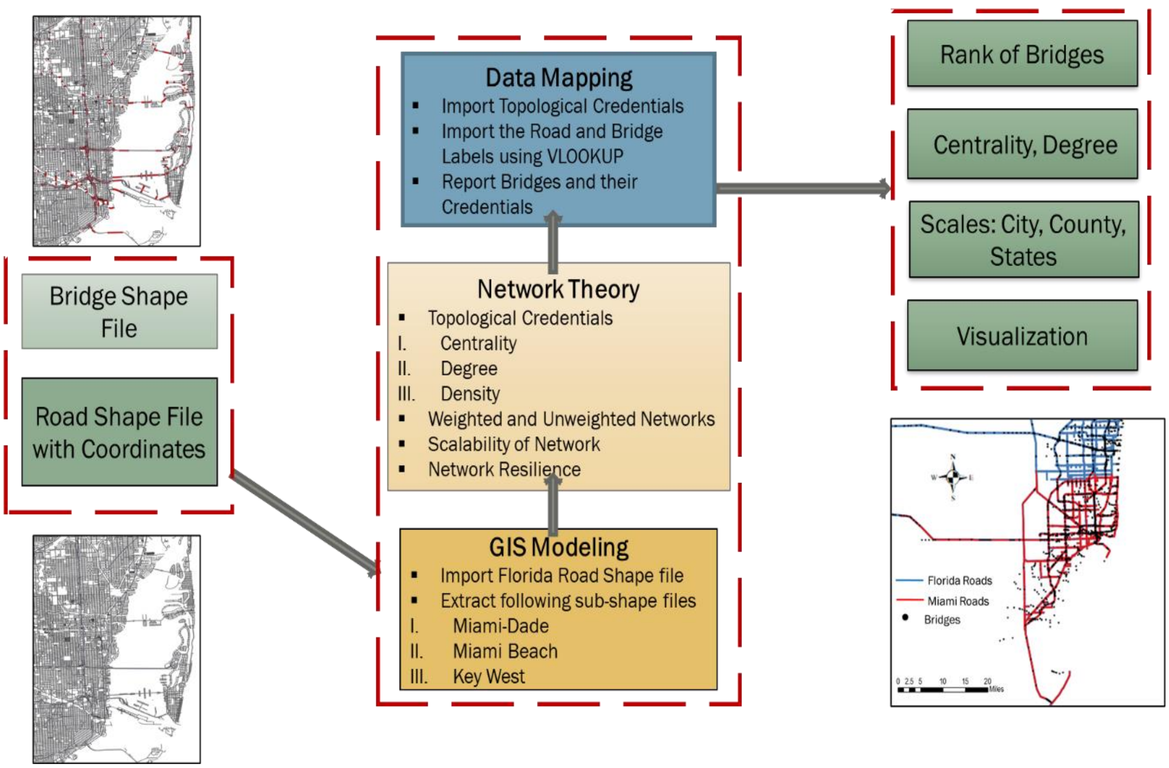


Figure 3: Methodological Framework of Identifying Critical Bridges of Road Network

3.3 Data Description

In this study, the Florida road network shape file is obtained from Florida Department of Transportation (FDOT) websites' Transportation Data and Analytics/GIS section (Figure 4). The Florida bridge shape file is also obtained from the same FDOT website (FDOT-GIS 2017).

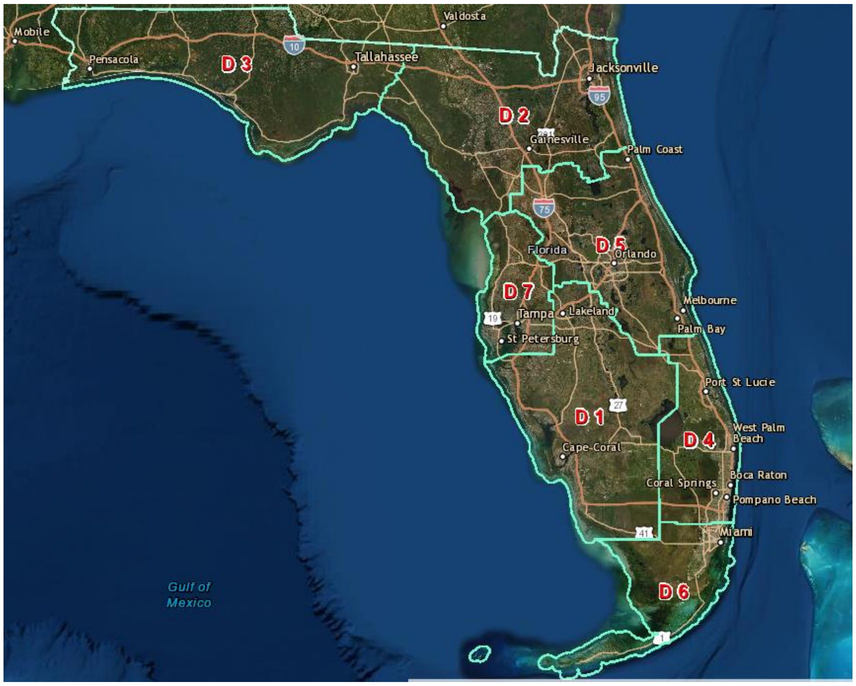


Figure 4 Florida Traffic Online- Source of Florida Road Network Shape File

Then, the Florida road-bridge network is extracted from the Florida road-bridge shape files using Geographic Information System (GIS) software. The shape file for the road network of Florida consists of all the freeways, highways, and arterials of the state. Besides, the Florida bridge shape file covers all the bridges on these highways, freeways, and arterials, respectively. The road network file is designed such a way that the roadways are divided in numerous sections, which are considered as links and the junction of the links (the end point of one link to the starting point of another link) are considered as nodes to generate the network graph as shown in Figure 5.

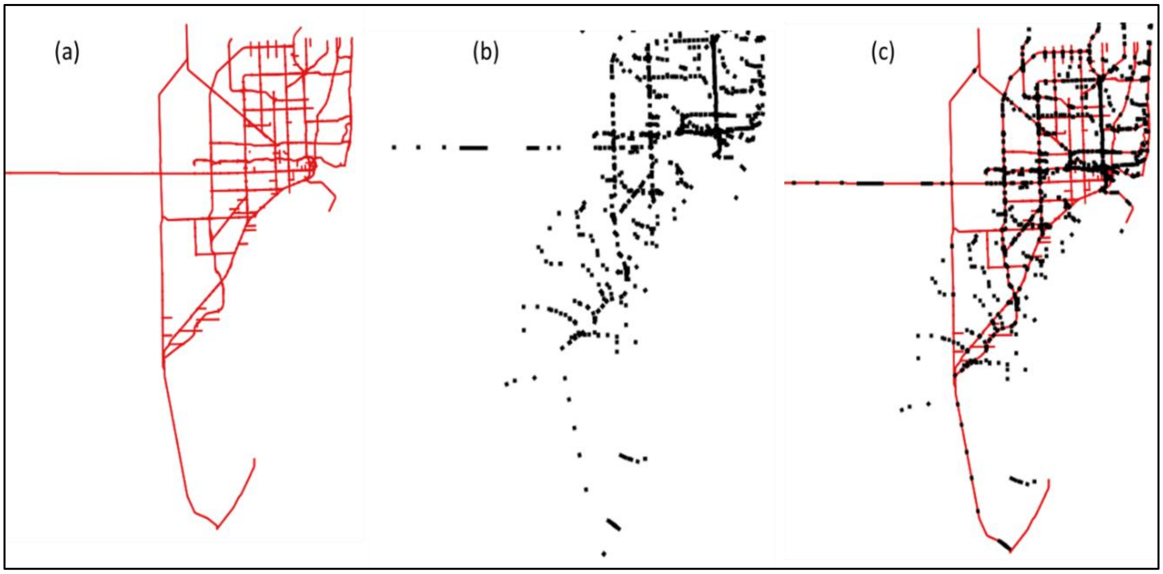


Figure 5: Example of Florida (Miami-Dade County) Road and Bridge Network. (a) Road Network, (b) Bridge Network, (c) Superimposed Road and Bridge Network.

3.3.1 Florida Road Network

The Florida road network shape file (Figure 6) is a polyline shape file and contains detailed information about the roadways. All the information is stored in a database which is accessible through the Attribute Table. From the shape file database, it was observed that the roadway names are available according to the road location and local place. Besides, the roadway numbers, assigned by FDOT are also available along with the county name, ZIP code and roadway direction (eastbound, westbound, southbound, and northbound).

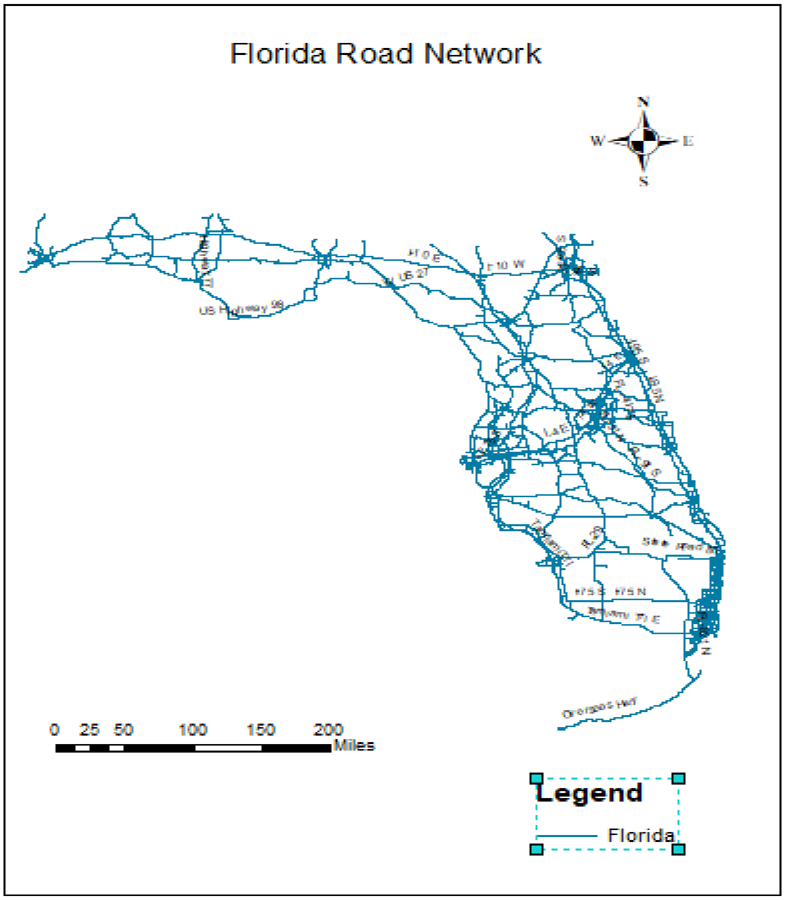


Figure 6: Florida Road Network

The most important information for the road and bridge network analysis is the specific geolocations (coordinates) of the starting point and end point of each roadway segment, which is available with the length of these segments. From the attribute table of the shape file, it is found that there are approximately 18,550 roadway segment and 15,550 roadway segment intersection information are existing in the shape file. Then, the route number (for an example the name of the 8th street is US 41 according to the route number), number of lanes and Average Annual Daily Traffic (AADT) counts are also obtainable from the attribute tables of the shape file.

3.3.2 Florida Bridge Network

The bridge shape file (Figure 7) for the Florida is also a polyline shape file which provides essential information for the bridge network analysis. The attribute Table of the shape file consists of the specific roadway numbers, through which the bridges can be specified along with the roadways. Besides, the structure number of each bridge assigned by FDOT, information about FDOT districts, county names and the length of roadways are also available. The most important information for the road and bridge network analysis is the specific geolocations (coordinates) of the starting point and end point of each link, which is available with the length of these segments.

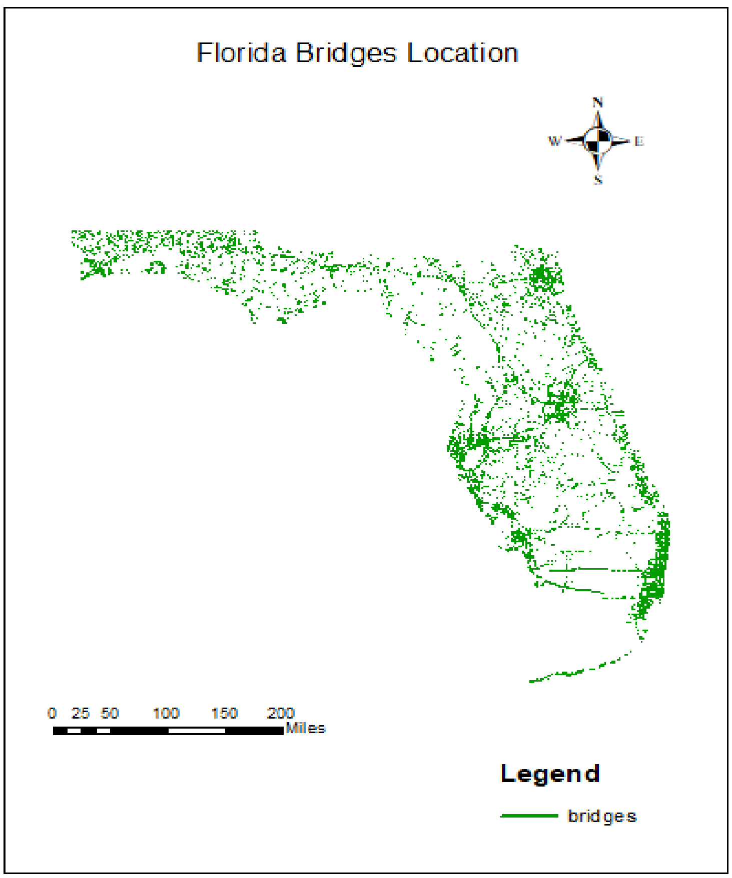


Figure 7: Florida Bridges Location

From the attribute Tables, it is found that there are approximately 18,550 links and 15,550 nodes information are existing in the Florida road shape file. Then, the route number (for an example the name of the 8th street is US 41 according to the route number), number of lanes, and Average Annual Daily Traffic (AADT) counts are also obtainable from the attribute Tables of the shape files.

3. 4 Network Analyses

The Florida road-bridge network analyses are performed at four scales as following order: (1) Key West; (2) Miami Beach; (3) Miami-Dade County; (4) Florida. While all the analyses results are tabulated in this study, interpretations of the analyses are provided for Miami-Dade County and Florida.

3.4.1 Key West Road-bridge Network

Unweighted analysis

Unweighted graph analysis only shows the effect of road-bridge network connectivity on different scale of the study area. As explained in previous section that the Florida road-bridge network is performed four scales, the Key West network is analyzed first. From key west road shape file, 50 roadway segments and 37 roadway segment intersection were found. After performing the Closeness Centrality analysis and mapping with bridges, 19 specific bridge location were found with centrality value. In Table 5, all the Key West bridge locations' Closeness Centrality values are orderly listed from highest to lowest. Then, the network analysis was performed for the link property by calculating Edge Betweenness Centrality. 25 roadway segments with bridges were found with centrality values after mapping with bridge shape file. In Table 6, all the Key West bridge segments Edge Betweenness Centrality values are orderly listed from highest to lowest.

Weighted Analysis

Weighted graph analysis reflects the effect of different weights (e.g., traffic count, volume, delay etc.) applied on the nodes and links along with the connectivity of the network. In this study, weighted analysis is performed only for links or roadways as the network parameter for nodes (closeness centrality) does not consider weights. Average Annual Daily Traffic (AADT), which is calculated by counting the total volume of vehicles of a road for a year divided by 365 days, is considered as weight on the roadways. For the Key West road-bridge network, weighted analysis did not show any differences in Edge Betweenness Centrality values and the results show a similar output as shown in Table 6. The reason behind this is the network topology and characteristics of the Key West road-bridge network as it is a long stretch at the southernmost part of the State of Florida as shown in Figure 8. As such, networks with more complex topology (i.e., grids, triangles) are likely to show more convincing changes in network credentials, which is not applicable for the Key West network. Such effects are presented in the following sections that include analyses of Miami-Dade County and Florida networks.

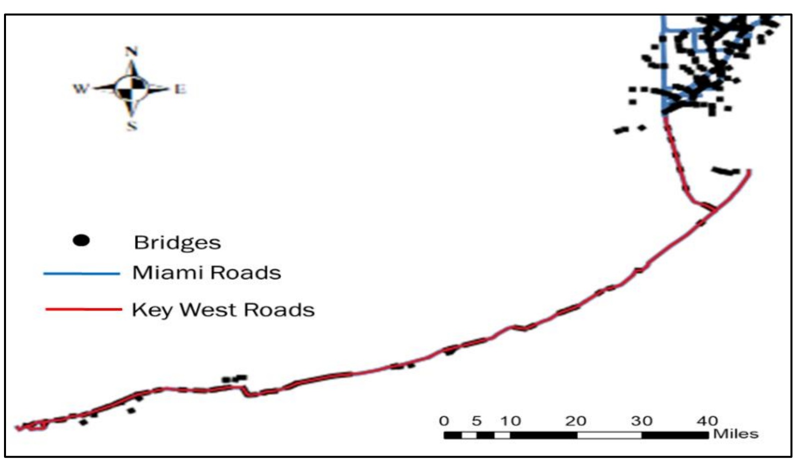


Figure 8: The Long Stretch of Key West Road-bridge Network

3.4.2 Miami-Dade County Road-bridge Network

Unweighted analysis

Unweighted graph analysis only shows the effect of road-bridge network connectivity on a different scale of the study area. From the Miami-Dade Road network file (Figure 9), 2199 links and 1960 nodes were found. After performing the Closeness Centrality analysis and mapping with bridges, 137 nodes connecting bridges were found with centrality value. The most 20 central nodes connecting bridges of Miami Dade county according to node property are listed in Table 7. Then, the network analysis was performed for the link property by calculating Edge Betweenness Centrality. 168 links with bridges were found with centrality values after mapping with bridge locations. The most 50 central bridges of Miami Dade County according to link property are listed below in Table 8.

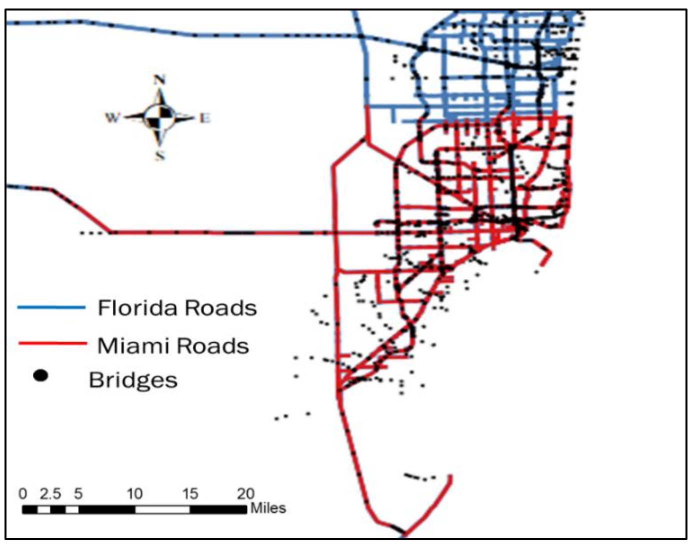


Figure 9: Miami-Dade County Road-bridge Network

Weighted Analysis

Weighted graph analysis reflects the effect of different weights (e.g., traffic count, volume, delay etc.) applied on the nodes and links along with the connectivity of the network. In this study, weighted analysis is performed only for links as the network parameter for nodes (closeness centrality) does not consider weights. Average Annual Daily Traffic (AADT), which is calculated by counting the total volume of vehicles of a road for a year divided by 365 days (Arafat et al. 2020), is considered as weight for the links. From the weighted Edge Betweenness Centrality results listed in Table 8, it can be said that traffic volume influences the network parameters significantly as the ranking of most central bridges changes after considering the impact of traffic on road-bridge network. For example, a bridge at Collins Avenue previously ranked as 10th most central bridge from unweighted analysis, but with the effect of traffic its' ranking as a central bridge's changes to 19. From Table 8, this type of changes in ranking of central bridges are found multiple times where some of the bridges' ranking increased and some decreased.

Previously (unweighted analysis) ranked as 24 (West Flagler Street) and 26 (Sunset Drive) central bridges' priority changes to 57 and 45 after considering the effect of traffic on the corresponding roadways. On the other hand, central bridges ranked as 46 (Caribbean Boulevard) and 47 (Marlin Road) from unweighted analysis are relocated in more central position of the Miami-Dade County road-bridge network with ranking of 23 and 25 respectively for weighted graph. Besides, the top 09 ranked bridges centrality values did not show any changes from unweighted analysis and the bridges ranked from 10 to 18 reflects minor changes in weighted analysis. The change in bridge ranking due to traffic is visualized in Figure 10, where the geolocation of bridge ranked as 22 from Table *8* (previously ranked as 20 in unweighted analysis) is highlighted.

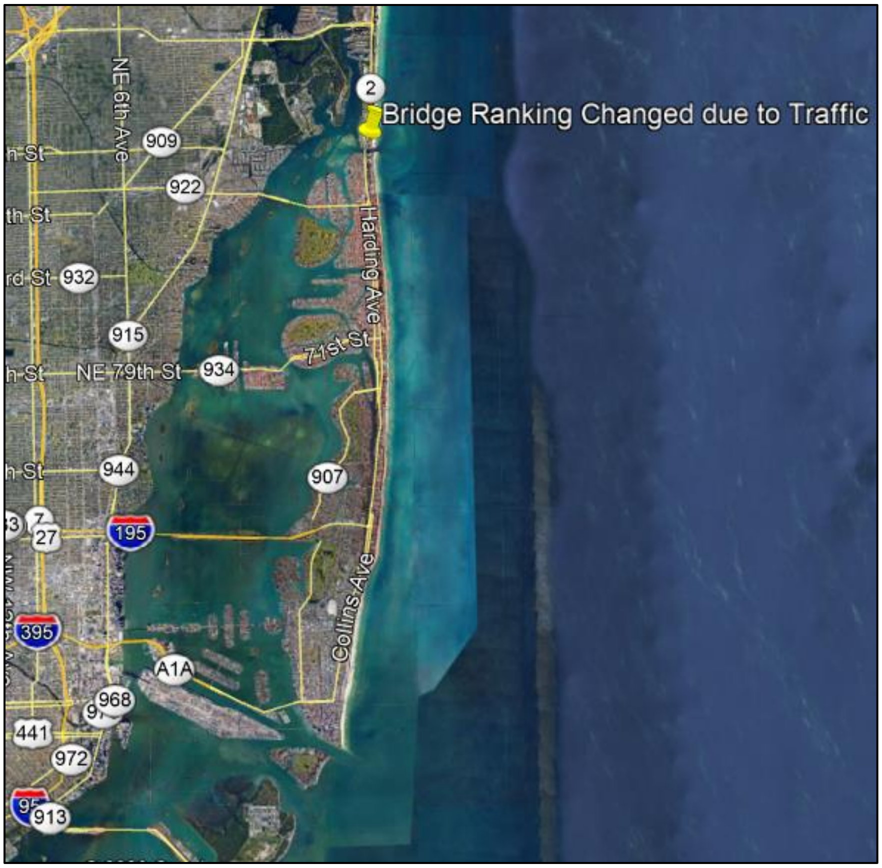


Figure 10: Change in Ranking of a Central Bridge of Miami-Dade County due to Traffic

3.4.3 Miami Beach Road-bridge Network Analyses

The Miami Beach network shape file (Figure 11), which is a subset of Miami-Dade County shape file consisted of 745 roadway segments and 678 roadway segment intersection. After performing the Closeness Centrality analysis and mapping with bridges, 107 specific bridge location were found with centrality value. From Edge Betweenness Centrality analysis, 134 roadway segments with bridges were found with centrality values after mapping with bridge shape file. As the number of specific bridge locations and bridge segments of Miami Beach and Miami-Dade County are very close, hence the results of Miami Beach network are only considered for scaling effect discussion.

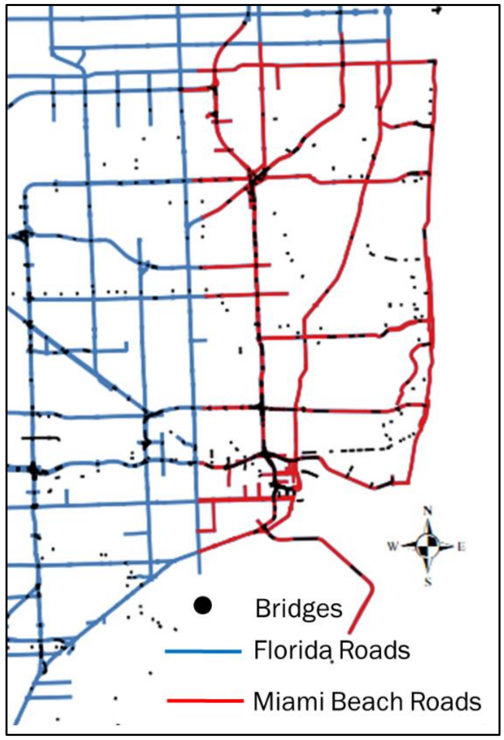


Figure 11 Miami Beach Road-bridge Network

3.4.4 Florida Road-bridge Network Analyses

Unweighted analysis

From Florida road network file (Figure 12), 18,462 links and 15,417 nodes were found. After performing the Closeness Centrality analysis and mapping with bridges, 2,444 nodes connecting bridges were found with centrality value. The most 20 central nodes connecting bridges of Florida according to node property are listed in Table 9. Then, the network analysis was performed for the link property by calculating Edge Betweenness Centrality. 3,252 links with bridges were found with centrality values after mapping with bridge shape file. The most 50 central bridges of Florida according to link property are listed in Table 10.

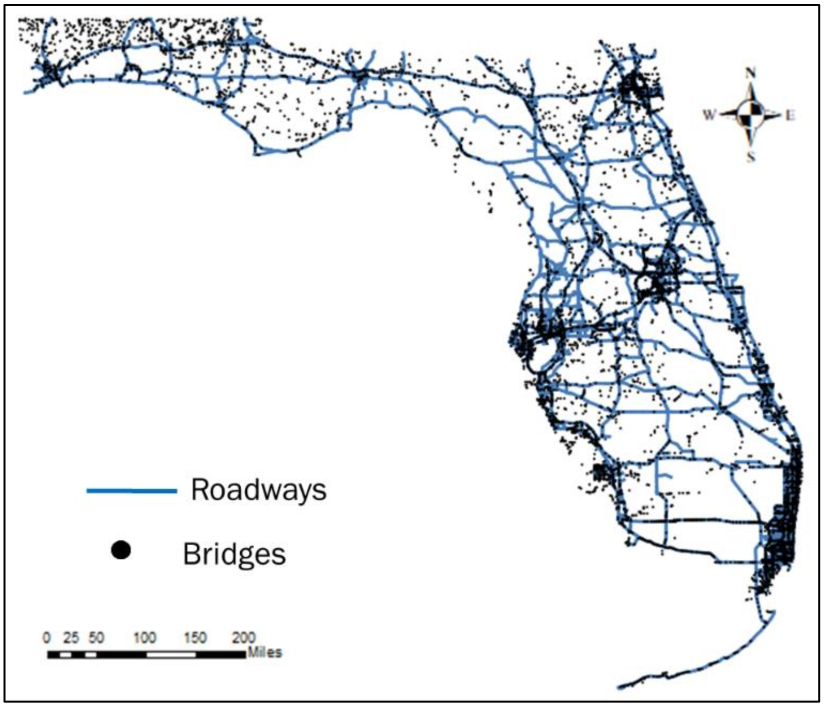


Figure 12: Florida Road-bridge Network

Weighted analysis

As weighted analysis is not applicable for Closeness Centrality (node property) network parameter, hence Weighted Edge Betweenness Centrality values (link property) are calculated for Florida road-bridge network. Similar to Miami-Dade County network, noteworthy changes in bridge ranking due to traffic is also observed and reported in Table 10, where the increase in bridge ranking due to traffic is marked in bold letter. For example, bridges ranking 10, 19, 42, and 44 in unweighted network got improved to 6, 11, 14, and 15 after considering traffic as weight. Besides, some other bridges ranked as 2, 5, 6, 29, 41, and 43 experienced a significant decrease in ranking due to traffic in weighted network analysis. These results and changes in bridge ranking clearly shows the impact of traffic volume on the road-bridge network along with the network connectivity.

3.4.5 Bridge Rankings at Different Scales

As Miami Beach and Miami-Dade County are subsets of Florida network, hence all the bridges of Miami Beach and Miami-Dade County are found in the Florida network analysis, but with different centrality values. This happens because of the scaling effect of the networks. The same bridge shows different centrality value at different scales of the network. The smaller the network size, the higher the centrality values of bridges. In Table ***11***, network scaling effect is shown for the nodes connecting bridges (Closeness Centrality) along with the respective bridge rankings of these networks, which clearly depicts higher centrality values for Miami Beach and Miami-Dade County network than the Florida network. Similarly, for the links with bridges (Edge Betweenness Centrality) of the network, scaling effect is also replicated in Table 12 where the centrality values of bridges for Florida network is smaller than the Miami Beach and Miami-Dade County network.

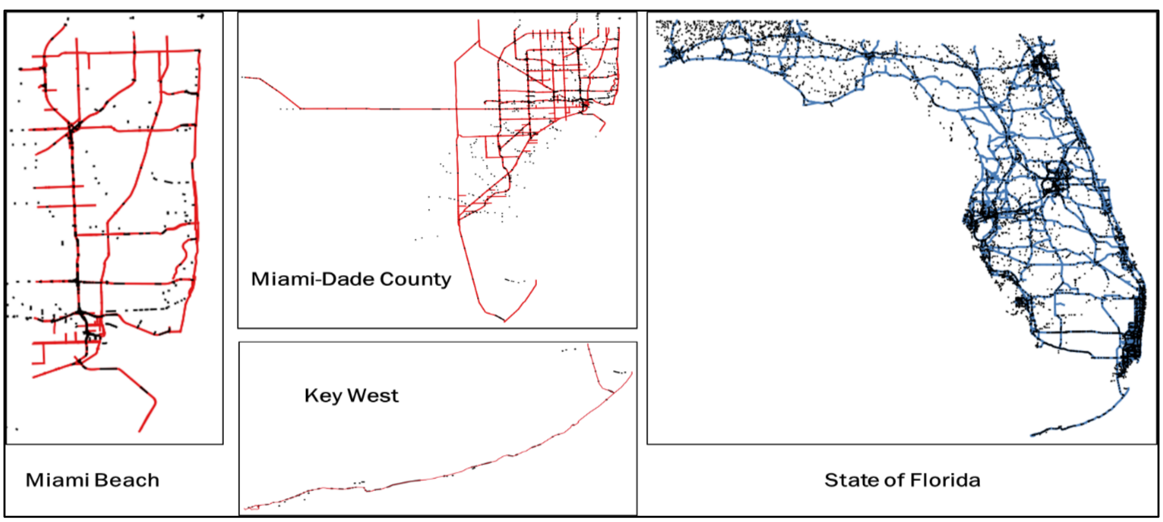


Figure 13: Key West, Miami Beach, Miami-Dade County and Florida Road-bridge Network

In both cases, Miami Beach network is considered as the base network for the comparison of centrality values and bridge rankings among three different scales. Figure

13 shows all the different scales used for the network analyses to explain the scaling effect in this study.

3.5 Application of Bridge Network Resilience

To understand the practical implication and significance of the proposed bridge ranking methodology, scenario analysis has been conducted with a sample (Sioux falls) road-bridge network (Bar-Gera 2016). The network (Figure 14) consists of 24 nodes (origin and destination), 76 links (roadways) and 5 bridges. The roadways are bi-directional meaning traffic can flow in both direction from origins to destinations. According to the origin-destination (OD) matrix (Table 14) of the Sioux falls network, 360,600 trips have been assigned among 552 OD pairs (Stabler 2020).

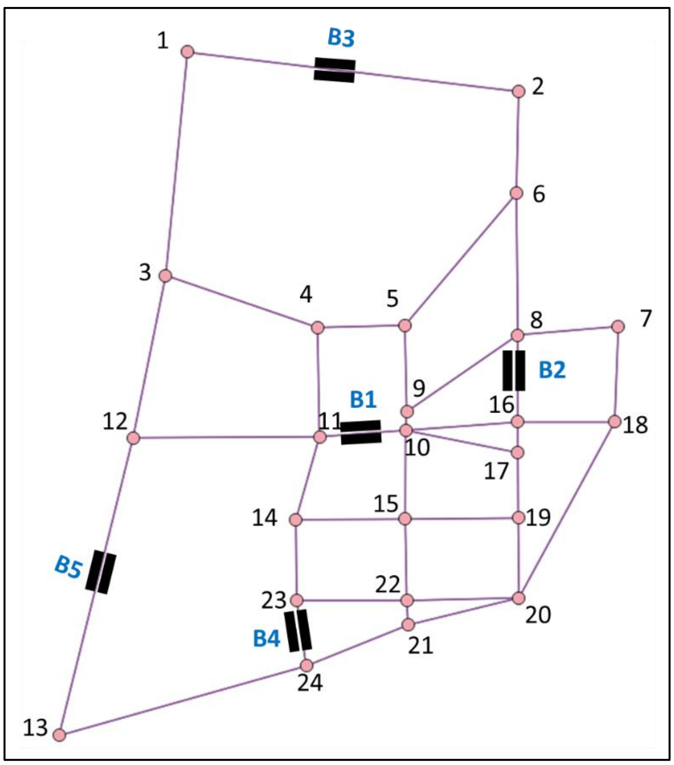


Figure 14: Sioux Falls Road Network- Base Case (Scenario 1)

The corresponding edge betweenness centrality (EBC) values of bridges (e.g., B1= 0.0769) are calculated by network analysis, which are defining the cruciality of the bridges and establishes the bridge ranking. From Figure 14, the most critical bridge of the network according to the EBC value is bridge B1 (0.0769), then B2 (0.0492) followed by B3 (0.0312). Hence, the bridge ranking is B1, B2, B3 for this network.

To observe the effect of removal of bridges due to any external event (e.g., maintenance, hurricane), average travel time for each link is calculated by applying static traffic assignment which follows user equilibrium method (Kumar and Peeta 2015; Sheffi 1985). Frank-Wolfe algorithm (Frank and Wolfe 1956) is applied to perform the user equilibrium traffic assignment with 250 iterations and BPR function (Roads 1964) is considered here as volume-delay function.

Now, using the AequilibraE python package (Camargo 2018) of QGIS software, the volume of traffic for each link is calculated from the demand of OD matrix, then the average travel time of the system for Sioux falls network is computed for different scenarios using the BPR function. To calculate the average travel time for each link, free flow travel times (minutes) and roadway capacities (vehicle per day) for different links of Sioux falls network are assumed (Bar-Gera 2016; Stabler 2020). Besides, the value for the constants of BPR equation, alpha is assumed 0.15 and beta is 4. Table 13 is showing the different free flow travel time, capacity, and length for each link along with nodes and links id.

3.5. 1 Scenario Analysis

To understand the essence of bridge network analysis through different network parameters (degree, centrality) explained before, three different scenarios are considered for the Sioux falls road network (Table 1). Scenario 1 (Figure 14) shows that all the five bridges of the road network are functional, and the system travel time is computed 669.903

minutes, which is considered as the base case. Then, scenario 2 is representing a disrupted situation of the network where three bridges (B1, B2 and B3) are inactive and a significant increase (31.55%) in system travel time (881.23 minutes) is found. Then, six different Schemes of scenario 3 (recovered network) are tested here to identify the impact of removal of different combinations of bridges. Scheme 4 is showing that when the most central bridge B1 is removed or inactive due to any external event, and the other two bridges (B2 and B3) are active; the system travel time increased substantially 23.45% with respect to the base case (scenario 1). Then, Scheme 5 and Scheme 6 are representing that only bridge B2 and bridge B3 is inactive and the increase in system travel time were found only 2.95% and 2.69% respectively in compared with the base case. Hence, it can be concluded by claiming that the inactivity of most central bridges is directly impacting the system travel time, hence defining the bridge ranking. For this case, the ranking of the bridges is B1-B2-B3. The other three Schemes (Scheme 1-3) are representing the other possible combination of bridges' inactivity and the impact on the road network which also supports the same bridge rank.

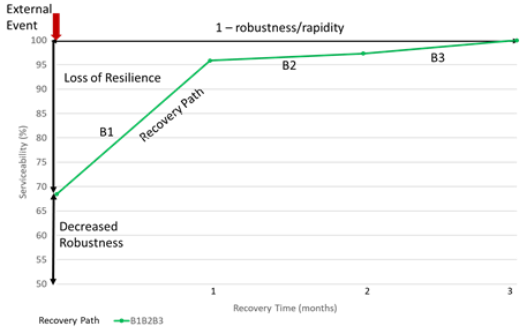
Table 1: Summary of Impacts of Different Scenarios

Scenarios and Schemes	Modifications in Network	System Travel Time (mins)	% Increase in STT (WRT base case)	Serviceability of network
Scenario 1	Base case-Fully functional bridge network	669.90	0	100
Scenario 2	Disrupted (3 bridges off) network	881.23	31.55	68.45
Scenario 3	Recovered Network (6 schemes)			

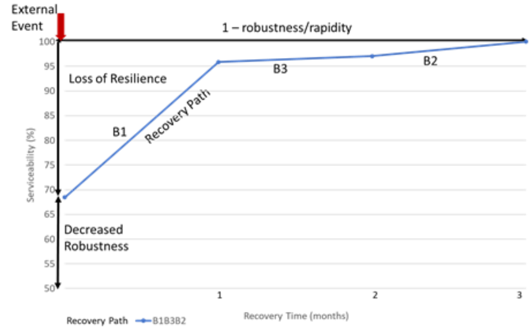
i) Scheme 1	Most central bridge (B1) is active, B2 and B3 are inactive	697.75	4.16	95.84
ii) Scheme 2	Less Central Bridge (B2) is active, B1 and B3 are inactive	865.86	29.25	70.75
iii) Scheme 3	Least Central Bridge (B3) is active, B1 and B2 are inactive	855.18	27.66	72.34
iv) Scheme 4	Most Central Bridge (B1) is inactive, B2 and B3 are active	827.01	23.45	76.55
v) Scheme 5	Less Central Bridge (B2) is inactive, B1 and B3 are active	689.68	2.95	97.05
vi) Scheme 6	Least Central Bridge (B3) is inactive, B1 and B2 are active	687.90	2.69	97.31

3.5.2 Network Resilience

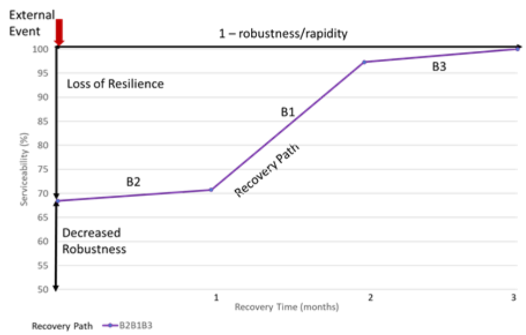
It is assumed that the percent increase in system travel time is inversely proportional to the serviceability of the network. As an example, for the disrupted network (scenario 2), the percent increase in system travel time is 31.55 with respect to the base case (scenario 1) which means the serviceability of the network is 68.45%. Figure 15 is depicting different recovery paths to restore the full serviceability of the network from external event by following the resilience triangle theory. Resilience triangle is defined by the robustness (related to serviceability) and rapidity (how fast a network can recover) of a system, where the area of the triangle represents the loss of resilience rather than resilience itself. Hence, the smaller the area of the resilience triangle, the system became less disrupted and more resilient (Bocchini 2014).



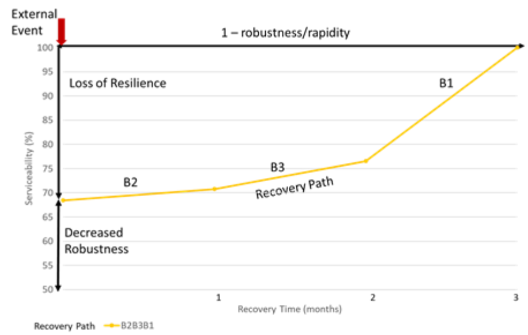
Recovery Path: B1-B2-B3



Recovery Path: B1-B3-B2

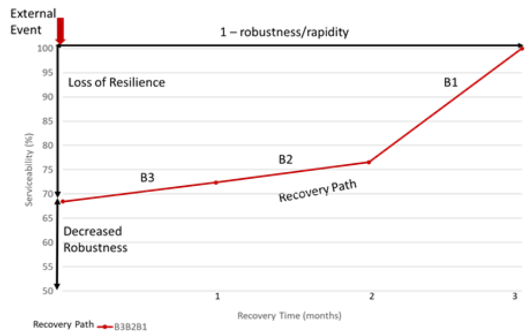


Recovery Path: B2-B1-B3



Recovery Path: B2-B3-B1

Recovery Path: B3-B1-B2



Recovery Path: B3-B2-B1

Figure 15: Recovery Paths to Enhance Resiliency of Bridge Network

From Figure 15, six recovery paths (in different colors) are observed which could be the possible recovery combinations of the three bridges. The Y axis shows the serviceability of the network in percentage and the X axis is the recovery time in months. Here, it is assumed that each bridge takes one month to restore its' operation to the full serviceability. Now, for the combination of bridge restoration of B1-B2-B3 (the recovery path in green color), the area of loss of resilience triangle found the smallest with respect to other five combinations. All the other possible combination of bridge restoration shows a larger area for loss of resilience triangle. Hence, it can be concluded that B1-B2-B3 is the optimum recovery path for this case.

3.5.3 Scaling Effects

Due to the change in network scale, topological credentials (i.e., centrality) of network also change accordingly and show different impacts on the network which is defined as scaling effect (Wei et al. 2014).

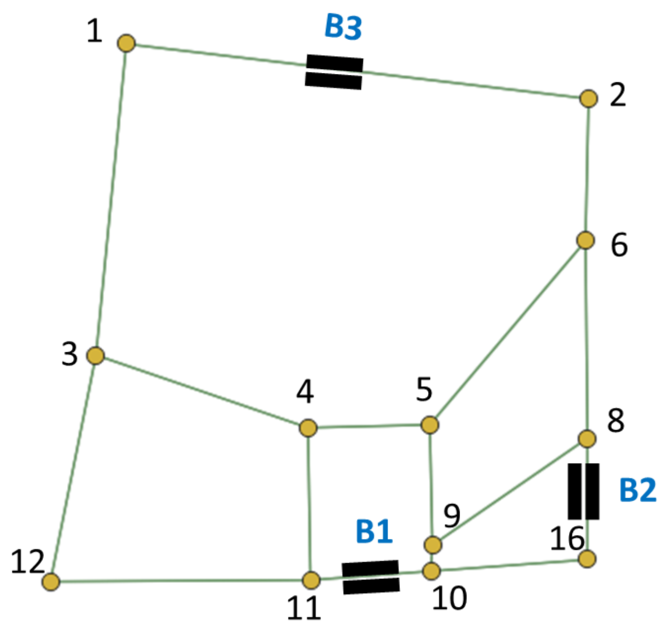
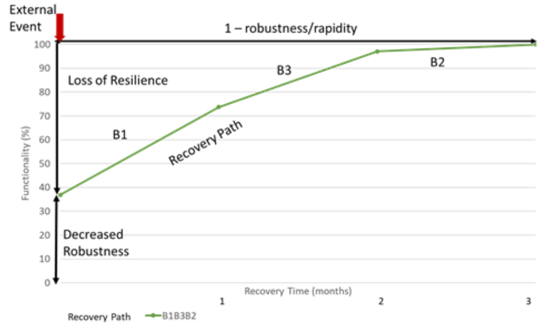
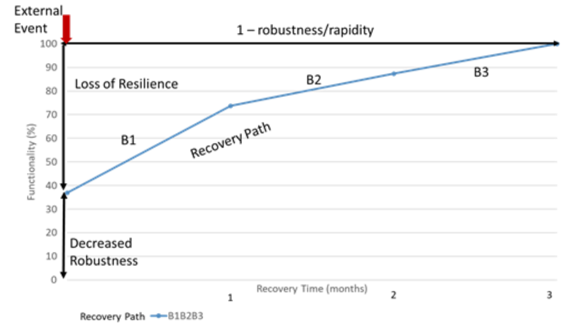


Figure 16: Sioux Falls Road Network (Small Scale)- Base Case (Scenario 1)

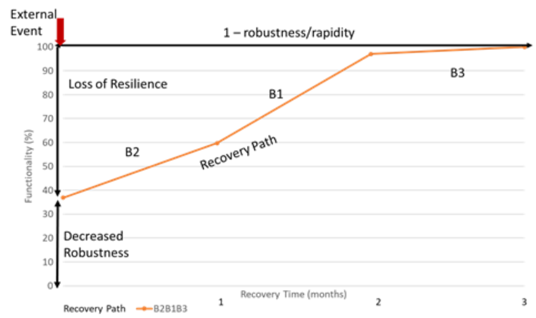
To observe the scaling effects (Hawick and James 2007; Louf et al. 2014) of the network, similar experiment (i.e., developing recovery schemes) is conducted at a smaller scale of the Sioux falls network. In this case, the Sioux falls network consists of 12 nodes and 32 links (Figure 16) with 3 bridges. Total number of trips for this scale are 98,400 and assigned among 132 OD pairs. Static traffic assignment is applied to quantify the flow of traffic in each link.



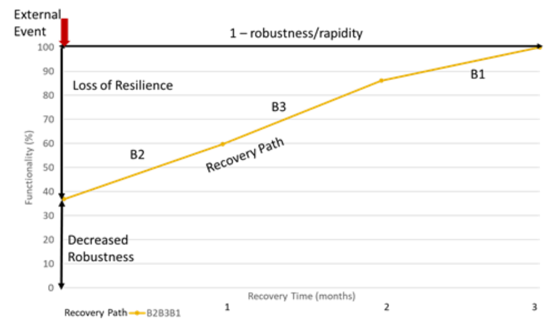
Recovery Path: B1-B3-B2



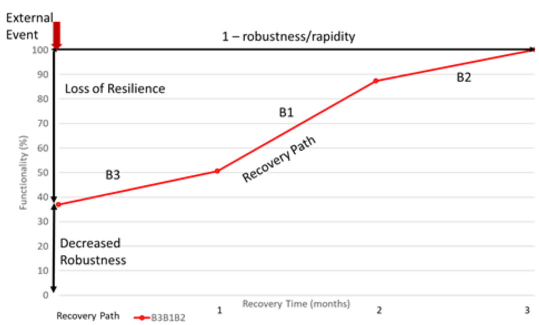
Recovery Path: B1-B2-B3



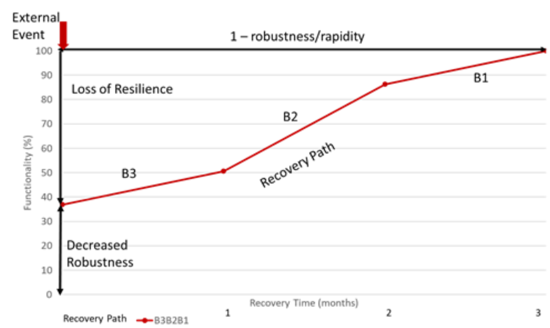
Recovery Path: B2-B1-B3



Recovery Path: B2-B3-B1



Recovery Path: B3-B1-B2

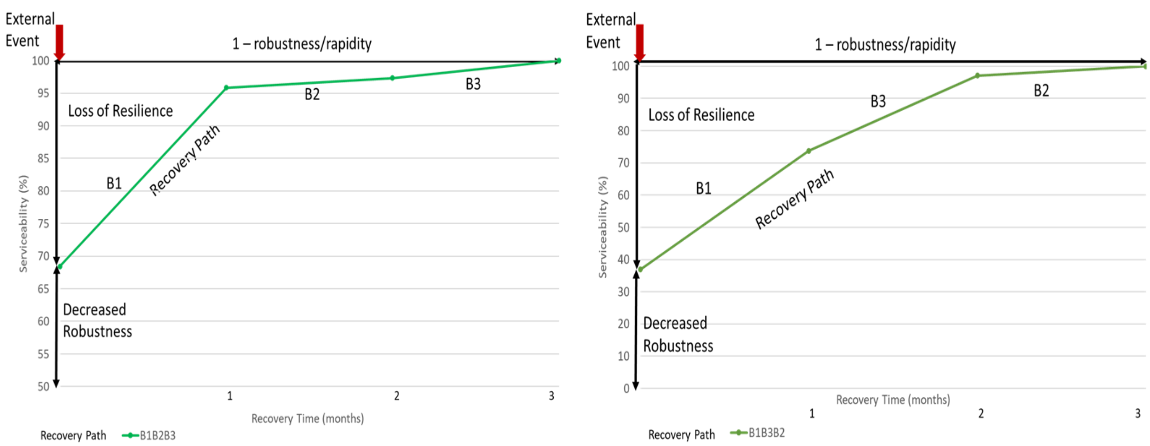


Recovery Path: B3-B2-B1

Figure 17: Recovery Paths to Enhance Resiliency of Bridge Network (Small Scale)

All the calculations for system travel time and serviceability of the network are the same as before. In Table 15, system travel time, percent change in system travel time and the reduction in serviceability due to removal of bridges are listed for three different scenarios and six schemes (scenario 3). Network analysis for this small scale showed that the edge bridge ranking is changed with respect to the full-scale analysis and now it is B1-B3-B2. From these results, six different recovery schemes (Figure 17) are developed again, and it showed that the most effective recovery scheme of bridges is now B1-B3-B2, previously which was B1-B2-B3. Hence, it can be concluded that due to the change in network scale, the impact of bridge removal changed on surrounding road network which is represented by the recovery schemes (Figure 17).

Now, the most efficient two recovery schemes (Figure 18) are identified at two different scales of Sioux falls network, which scale should be chosen to enhance the network resiliency is a crucial question.



Larger network recovery scheme

Smaller network recovery scheme

Figure 18: Comparison of Most Efficient Recovery Schemes of Two Scales (Sioux Falls)

To answer this, following justifications are listed to select the recovery scheme of larger network over the smaller one-

- The larger network experiences less increase in system travel time after disruption (i.e., inaccessibility of bridges) with respect to the smaller network.
- For the most efficient recovery schemes of both networks, the area of resilience triangle (i.e., loss of resilience) is smaller for larger network. In Figure 18, area of the resilience triangle for larger network is 24 and for smaller network is 61.

- Larger network serves more zones (24 zones) and roads (76 links) than the smaller network, hence considering recovery scheme of larger network will benefit more people.
- Robustness (i.e., loss of serviceability based on percent increase in system travel time) of the larger network is higher than the smaller network.
- Recovery scheme is more reliable for larger network as after restoring the first bridge, the system regains 95% serviceability, whereas for smaller network, the recovered serviceability is 73%.
- The slope of recovery for larger network is steeper, which means the rate of recovery of larger network is higher than the smaller network.
- Overall, the larger network is more resilient in terms of robustness and recovery of the network.

3.6 Discussion of Results

Enhancing resiliency of physical infrastructure systems is becoming a growing concern for researchers, practitioners, and policy makers as it affects the society significantly. The main objective of this study is to develop a systemic approach to enhance the infrastructure system resiliency by identifying and prioritizing the topological credentials of infrastructure components (i.e., bridges of road network) through network science principles. Hence, the Florida road-bridge network is considered here and analyzed at four different scales. All results from the network analyses listed in the previous section are representing the most influential, vulnerable, and critical bridges for both weighted and unweighted network. To quantify this phenomena, node level property and link level property of the network are measured by Closeness Centrality and Edge Betweenness

Centrality. Table 5 to Table 10 are representing the ranking of most important bridges of the respective unweighted/weighted networks from high to low. Furthermore, Table 8 and Table 10 are showing the effect of traffic along with the network connectivity on bridge ranking as well as the changes in priority due to traffic volume.

To develop a systematic sequencing of the bridge construction or maintenance work, Closeness Centrality (Table 5, Table 7, Table 9) should be considered for nodes connecting bridges, such as road-bridge intersecting point or bridge segment joints. Besides, Edge Betweenness Centrality (Table 6, Table 8, Table 10) should be considered while links with bridges are the point of interest for weighted/unweighted networks. To consider the effect of traffic along with network credentials on bridges, ranking of bridges from Table 8 and Table 10 should be taken into consideration.

Normally every two years, the bridges in the United States are inspected for regular maintenance purposes. Sometimes, due to time and budget constraints, inspection of all the bridges may not be possible in a timely manner, hence the maintenance work delays. As a result, the bridges that are critical for the road network remain undermined. If these critical bridges are removed from the road network, most of the surrounding routes of the network will be affected, resulting in increased travel time and vehicle delay, hence decrease the resiliency of road network. By applying the rank of critical bridges, practitioners can approach systematically while performing the maintenance of the existing bridges. To understand the practical implication of the proposed method of bridge ranking, scenario analyses (with and without critical bridges) of a sample (Sioux Falls) road-bridge network are performed to quantify the user optimal travel time. Here, static traffic assignment is applied by considering Frank-Wolfe algorithm and the Bureau of Public Roads (BPR) function, which measured the improvement of the system serviceability (system travel time and cost) and recovery (resilience) of the bridge network.

The proposed methodology of identifying central or critical bridges could also be useful for new bridge construction according to the bridge construction guideline (Mehrabi and Torrealba 2019). As bridges are a part of road networks, the most critical roadways may also be found by following the similar network analysis. After identifying the central roadways which could be connected by bridges, the construction of these new bridges can be prioritized over the other new bridge construction. By doing so, the serviceability of bridges which connect most central roadways could improve, i.e., reduction in total system travel time and vehicle delay for different origin-destinations as well as the time-cost value of the construction, finally improving the resiliency of the road network. The contributions and findings of this research are listed below:

- This study developed a framework to identify the topological credentials (i.e., centrality) of physical infrastructure components (i.e., roads, bridges) based on their connectivity and attributes (i.e., weights) of the network. To do so, centralities of bridges for Florida and Sioux Falls road networks are identified considering vehicular traffic (i.e., AADT) as a weight.
- Network experiments are performed at different scales (i.e., city, county, state) and results showed that the same infrastructure components carry a different level of importance at different scales of the network. In this study, changes in bridge ranking (based on edge betweenness centrality) are observed for both Florida and Sioux Falls network at different scales.

- This research developed systematic recovery schemes (sequential restoration) of infrastructure components considering topological credentials and attributes of the network to restore the full serviceability from disruptions. The network in Sioux Falls is investigated in this research to develop recovery schemes for three bridges' disruption.
- Scaling effect is observed for the transportation networks after developing the recovery schemes. The network experiment in Sioux Falls showed that the efficient recovery schemes changed at different scales.
- The comparison between efficient recovery schemes at different scales of the transportation network (i.e., Sioux Falls) showed that the larger network ensured a more resilient system than the smaller network.

CHAPTER 4

IMPROVING SEVICEABILITY OF TRANSPORTATION NETWORK

4.1 Background

Recent advancements in network science showed that the topological credentials of the elements (i.e., nodes and links) in a network carry important implications. Likewise, roadway segments (i.e., links) and intersections (i.e., nodes) in a road network should be assessed based on their position in the network at a given geographic scale. The goal of this study is to present a framework that can identify and select critical nodes and links in a road network based on their topological credentials (i.e., centrality). Moreover, the effects of systematic interventions conducted on such nodes and links in improving overall system serviceability (i.e., reduced vehicular delay and travel time) provide an adequate level of service (LOS). A real-world road network (downtown Boise) is investigated by applying lane interventions on roadways experiencing similar level of congestion. To quantify the serviceability of the road networked system, microscopic traffic simulation and analyses are conducted.

It is critical to know which components are most significant to the overall network's success (Mortula et al. 2020), and therefore vulnerable to disruptions (Sadri et al. 2021), when designing and managing networked systems. Even though reliability of networked system is extensively studied, few studies have been found that assess the components of vulnerability in the context of the enhancing the serviceability of networked systems (Barker et al. 2013; Baroud et al. 2014; Wan et al. 2018).

In transportation planning and forecasting, microscopic simulation is regarded as a credible technique for traffic study (Arafat et al. 2020). VISSIM, the state-of-the-art microscopic traffic simulation tool, is used for different studies in transportation domains such as automatic signal timing decision to reduce traffic congestion (Tariq et al. 2020), prediction of traffic diversion due to incidents on freeways (Saha et al. 2020), and active traffic management for connected vehicles (Saha et al. 2020). In addition, transportation system operation and management (TSMO) and intelligent transportation system (ITS) related studies have also used microscopic simulation extensively (Saha 2019).

For road networks, some critical intersections (nodes) and roadways (links) may become congested and inapproachable for adjacent traffic, resulting in significant decrease in the level of service (LOS) as well as reduction in the roadway capacity. Hence, the goal of the study is to develop a systematic strategy to improve the serviceability of road networked systems by applying design interventions on critical components. The objectives to enhance the goal are as follows:

- Identify the most critical nodes (intersection) and links (roadway) of the road networks.
- Outline specific interventions (e.g., increasing roadway capacity by adding lane) to implement on critical road network components (e.g., roadways).
- Quantify and compare (roadways which experience similar level of congestion) the improvement in serviceability at system-level of the road network.

To achieve these goals and objectives, the following research questions are explored as listed below:

- On which network components (i.e., links experiencing a similar level of congestion) should interventions be implemented?

- Applying interventions on critical components, how much improvement in serviceability of road network can be achievable?

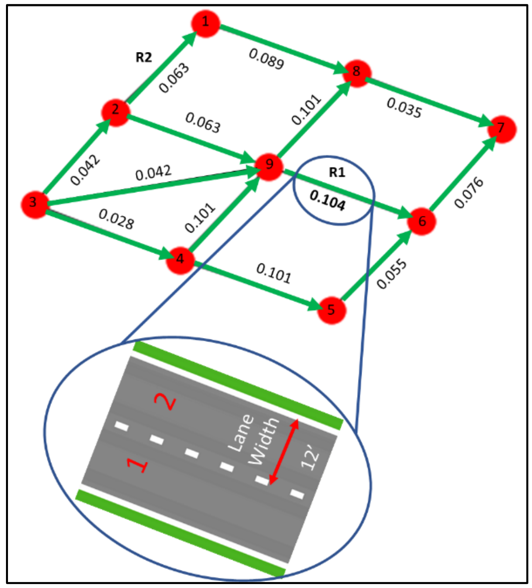


Figure 19: Hypothetical Road Network for Lane Intervention to Improve Serviceability of the System

Figure 19 is representing a hypothetical road network where two roadways (R_1 and R_2) are experiencing similar level of congestion (e.g., LOS E). Now, lane interventions (e.g., increasing lane width, adding lane) could be applied to both roadways, but may not improve the serviceability of the road networked system equally. Hence, identifying the critical roadway based on the network topology (i.e., centrality, R_1=0.104 and R_2=0.063, hence R_1 is more critical) and implementing lane intervention on R_1 could better improve the serviceability of the road networked system.

The core contribution of this study is to develop a methodology to improve serviceability of the road networked system by implementing lane interventions on critical roadways. The research will help to decide on which roadways (having a similar level of service) lane interventions should be implemented by using complex network metrics

(Boccaletti et al. 2006; Strogatz 2001). The study has developed a systematic strategy to enhance road network serviceability, helping traffic managers and practitioners establish an efficient plan for transportation system development and operational works.

4.2 Road Network Data

For this study, a real-world road network (Boise downtown) is considered for both network analyses and traffic simulation studies, which is already created by state-of-the-art microscopic traffic simulation software (VISSIM) developers. In following Figure 20, the Boise Road network is shown with hypothetical labelling on intersections. The whole network has 55 nodes (intersections) and 84 links (road segments). Most of the roadways are one way here as it is representing a road network of a downtown city area (Boise, Idaho). The signalization system for the road network is ring barrier controlled (RBC), and some of the intersections are actuated. Besides, Vehicles are assigned among 140 origins and 363 destinations using the static traffic assignment method. The detailed information of the Boise downtown roadway characteristics is listed in Table 2.

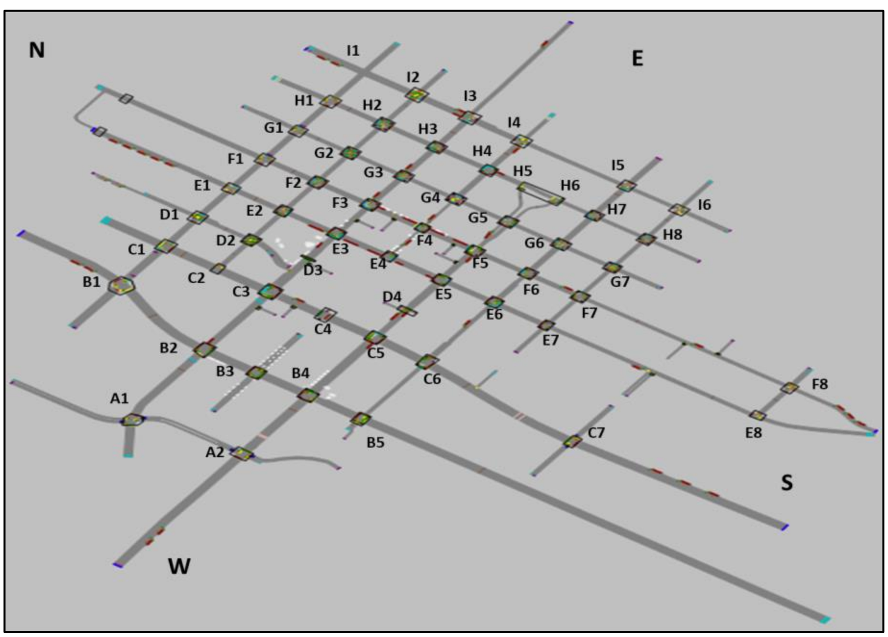


Figure 20: Boise Downtown Road Network with Hypothetical Labelling

Table 2: Boise Roadway Characteristics

From Node	To Node	Link Type	Traffic Flow Direction	No of Lanes	Traffic Volume (vph)	Vehicle Speed (mph)
B1	B5	One-way	Southbound	5	2208	35
C7	C1	One-way	Northbound	5	2460	35
D1	D2	One-way	Southbound	1	101	30
D2	D1	One-way	Northbound	1	116	30
D3	D2	One-way	Northbound	2	229	30
D2	D3	One-way	Southbound	1	275	30
E1	E3	One-way	Southbound	3	764	30
E3	E5	One-way	Southbound	4	764	30
E5	E7	One-way	Southbound	3	764	30
E7	E8	One-way	Southbound	2	764	30
F3	F1	One-way	Northbound	3	355	30
F5	F3	One-way	Northbound	4	355	30
F7	F5	One-way	Northbound	3	355	30
F8	F7	One-way	Northbound	2	355	30
G7	G1	One-way	Northbound	1	299	30
G1	G7	One-way	Southbound	1	186	30
H5	H1	One-way	Northbound	3	258	30
H8	H5	One-way	Northbound	2	258	30
I1	I4	One-way	Southbound	2	670	30
I4	I1	One-way	Northbound	2	486	30
I4	I6	One-way	Southbound	1	670	30
I6	I4	One-way	Northbound	1	486	30
E7	I6	One-way	Eastbound	2	267	25
I5	E6	One-way	Westbound	3	969	25
E6	B5	One-way	Westbound	2	969	25

A2	C5	One-way	Eastbound	4	2019	25
C5	F5	One-way	Eastbound	3	2019	25
F5	H5	One-way	Eastbound	1	1009	25
F5	H6	One-way	Eastbound	1	1010	25
G4	I4	One-way	Eastbound	3	406	25
G4	E4	One-way	Westbound	1	64	25
E3	A1	One-way	Westbound	4	800	25
I3	E3	One-way	Westbound	3	800	25
C2	I2	One-way	Eastbound	1	78	25
I2	C2	One-way	Westbound	1	93	25
C1	B1	One-way	Westbound	2	97	25
B1	C1	One-way	Eastbound	2	173	30
E1	C1	One-way	Westbound	1	133	25
C1	E1	One-way	Eastbound	2	173	30
E1	F1	One-way	Eastbound	3	227	25
F1	G1	One-way	Eastbound	3	280	25
G1	I1	One-way	Eastbound	3	540	25

4.3 Methodology

Network analysis and traffic vulnerability assessment (by microscopic traffic simulation and analysis) for a real-world road network (Boise Road network) are being conducted in this approach. Different network metrics at node level (betweenness centrality, closeness centrality) and link level (edge betweenness centrality) are computed and prioritization of those centrality values identified the most critical intersections and roadways. Then, implementation of different measures to improve the serviceability (travel time and vehicle delay) of critical intersections and roadways are applied which led to enhance efficiency of the system. Finally, the system performance is measured in terms of travel time, vehicle delay, and level of service (LOS). According to Highway Capacity Manual, the level of service is defined as a qualitative measure of the level of quality of traffic flow, and the quality is measured based on performance measures which attempt to assess the comfort of the road users. LOS is categorized into six classes (LOS A to LOS F); where LOS A is the free-flow condition, LOS E is the congested situation when traffic flow is at the roadway capacity (maximum traffic flow), and LOS F is over-capacity.

In this study, two basic network metrics i.e., betweenness and closeness centrality are used to identify the critical components of road network. Betweenness defines a central node (for link it is edge betweenness) which lies mostly on the shortest path of other pairs of nodes. Closeness defines a central node which is close, on average, to other nodes. Besides, with the help of the state-of-the-art microscopic traffic simulation software VISSIM, a real-world road network (Boise downtown road network) (Abdel-Rahim et al. 2006; Zhao et al. 2010) is analyzed by computing travel time and vehicle delay for high demand origin-destination pairs. Besides, network analyses of the same road network are performed to identify the critical intersections and roadways. After implementing different measures on these critical components, the travel time and vehicle delay are calculated again and finally compared with the congested case to identify the improvement of the level of service (LOS) of the road network. As Boise Road network is already a well-established and tested road network, hence the calibration and validation of this road network were not performed.

4.4 Road Network Analysis

The network analysis for Boise downtown road network is conducted in two ways. For node (intersection) level property and for link (roadway) level property. The Figure 20 shows the hypothetical labelling on the road network for the analyses. The results for weighted directed graph analyses of Boise Road network are listed below for different node (Table 3) and link (Table 4) properties.

Table 3: Node Property Analyses of Boise Downtown Road Network

Rank	Node	Closeness Centrality	Node	Betweenness Centrality
1	F3	0.1741	G3	0.2300
2	E3	0.1726	E5	0.2237
3	E4	0.1726	C3	0.2170
4	F2	0.1712	C5	0.2029
5	F4	0.1704	F3	0.1781
6	G5	0.1704	E6	0.1766
7	E5	0.1697	F5	0.1643
8	C3	0.1690	E3	0.1640
9	D3	0.1649	G5	0.1535
10	H5	0.1623	H3	0.1452
11	H6	0.1617	H4	0.1431
12	E6	0.1598	C2	0.1231
13	F5	0.1598	H5	0.1200
14	H4	0.1592	G2	0.1197
15	H2	0.1518	F6	0.1151
16	F1	0.1498	G4	0.1133
17	G7	0.1498	F2	0.1121
18	G2	0.1488	E4	0.1104
19	G3	0.1477	C6	0.1090
20	B2	0.1466	D3	0.1058

Table 4: Link Property Analyses of Boise Downtown Road Network

Rank	From Node	To Node	Edge betweenness centrality	Rank	From Node	To Node	Edge betweenness centrality
1	H4	H3	0.1386	26	E6	E7	0.0833
2	C3	C2	0.1344	27	E3	E4	0.0790
3	H5	H4	0.1324	28	F5	F4	0.0786
4	H3	G3	0.1322	29	H6	H5	0.0774
5	G3	G4	0.1250	30	G5	G6	0.0771
6	E4	E5	0.1232	31	F4	F3	0.0740
7	D3	C3	0.1187	32	B3	B4	0.0713
8	E5	E6	0.1180	33	F7	F6	0.0703
9	E5	F5	0.1144	34	B2	B3	0.0703
10	G3	F3	0.1135	35	F6	E6	0.0680
11	C6	C5	0.1101	36	G4	G5	0.0671
12	D4	E5	0.1082	37	F3	F2	0.0670
13	C5	D4	0.1072	38	H7	H6	0.0667
14	C4	C3	0.1062	39	G7	H8	0.0636
15	G2	G3	0.1053	40	C1	D1	0.0598
16	C5	C4	0.1052	41	F6	F5	0.0597
17	F3	E3	0.1046	42	E2	F2	0.0569
18	E6	C6	0.1037	43	G6	F6	0.0564
19	B4	C5	0.1012	44	G5	H5	0.0540
20	F5	G5	0.0966	45	E7	F7	0.0530
21	E3	D3	0.0958	46	E2	E3	0.0523
22	F2	G2	0.0924	47	F1	G1	0.0510
23	C3	B2	0.0915	48	C2	C1	0.0507
24	D2	E2	0.0848	49	H8	H7	0.0485

25	C2	D2	0.0847	50	F4	E4	0.0432

4.5 Traffic Simulation Results

To quantify the serviceability of the road network in terms of travel time, vehicle delay and level of service, the state-of-the-art microscopic traffic simulation software VISSIM is used for this study. VISSIM is a microscopic traffic simulation software that is commonly used to evaluate traffic conditions. It's particularly useful for comparing multiple traffic management situations before settling on the right alternative and optimization steps (Lin et al. 2013).

4.5.1 Initial Simulation Criterions

To understand the effect of different interventions on road network, initially a congested road condition is created for Boise downtown road network by increasing the traffic volumes (from the default traffic volume shown at Table 2) of some specific road segments. The basic simulation parameters are explained below (Turner 2015):

Period: The period of time to be simulated. Including initialization period.

The simulation is considered to run for 4500 seconds (1.25 hours) and the initial 900 seconds is considered as initialization period (as the whole network requires this time to show the complete effect of the traffic while measuring the travel time and vehicle delay).

Simulation resolution: The number of times the vehicle's position will be calculated within one simulated second (range 1 to 10). The higher the value the smoother the simulation. A value of 10 is used for this study.

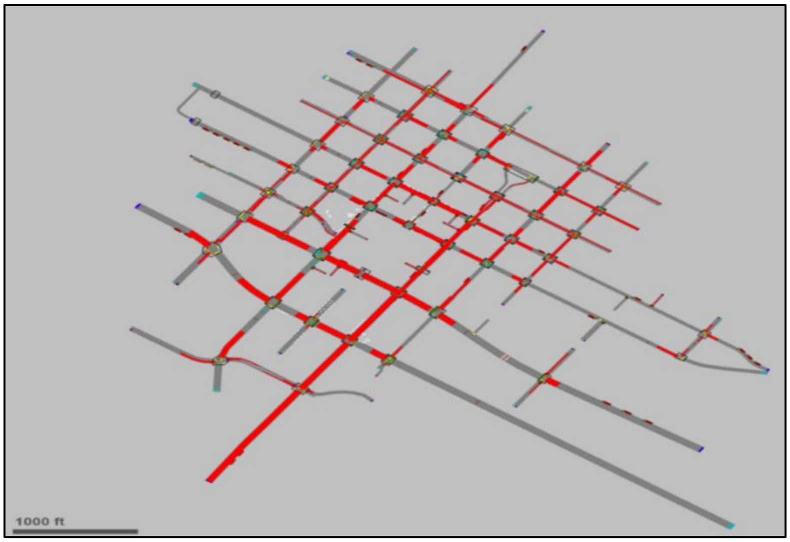


Figure 21: Boise Downtown Road Network (Congested Case)

Random Seed: Simulation runs with identical input files and random seeds generate identical results. For this study, an initial value of 70 is used and an increment value (random seed increment) of 5 is considered for simulating different scenarios. Besides, 10 simulation runs are performed for each scenario.

4.5.2 Interventions to Improve System Serviceability

Different interventions for intersections and roadways may contribute to improve the total system travel time and vehicle delay, hence the level of service of the road network. The design intervention i.e., increasing number of lanes, applied only on roadway segments (link-level) in this study. The implementation of intervention is focused on following criterions-

1) Interventions should be applied on the roadway segments having the same level of service (e.g., LOS F) to compare the before and after scenario of implementing design interventions.
2) Equitable improvement (e.g., for the same length of the roadway, add an equal no of lanes) should be considered for all the modified scenarios.

Scenario- Both Roadway Segments are Along the OD Routes and Same Direction

Initially, a congested scenario is generated by increasing the traffic volume of the road network. The traffic simulation is performed using VISSIM by following the *initial simulation criterions* mentioned earlier. The congestion level of roadways (B4-C5, E5-F5) are identified after simulating the base case. For motorized vehicle, travel speed is used to characterize vehicular LOS for a given direction of travel along an urban street facility (Elefteriadou 2016). In this case, the base free flow speed of both roadway segments is 25 mph. Besides, the critical or central roadways are determined based on the edge betweenness centrality values (Table 4) as all the interventions are applied at link-level.

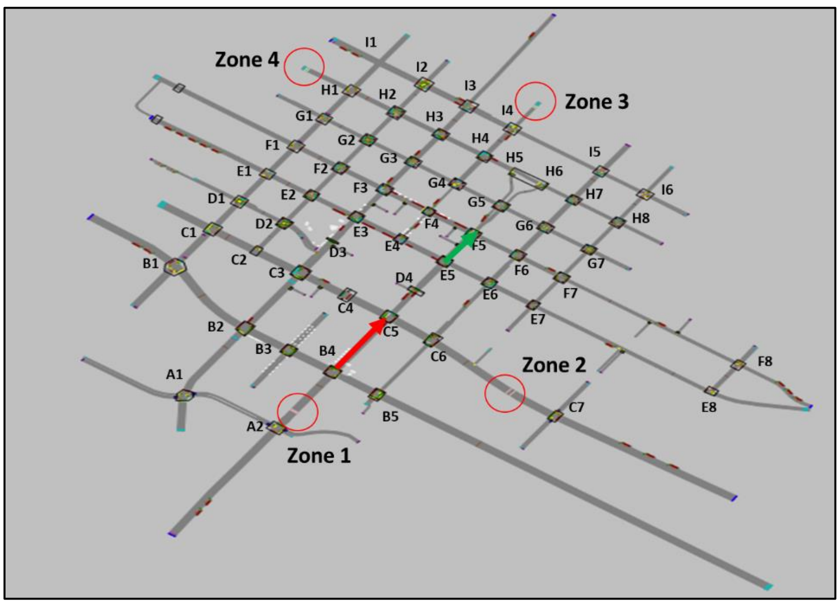


Figure 22: Boise Downtown Road Network (Experimented Roadway Segments)

The average travel time and vehicle delay are computed for the four OD pairs (zone 1 to 3, zone 1 to 4, zone 2 to 3 and zone 2 to 4) as shown in Figure 23. These four OD pairs are selected based on the high demand and flow of traffic from the origins to destinations. The design intervention, i.e., increasing (adding one lane) number of lanes is applied on congested roadways. For this scenario, the intervention is applied on two roadway segments in same direction and experiencing same level of congestion. The roadways B4-C5 (less central) and E5-F5 (more central) are found experiencing level of service F and these two roadway segments (Figure 22) are considered for equitable improvement (for the same length of the roadway, adding one lane). Here, B4-C5 and E5-F5 are one-way roads (eastbound) having 4 and 3 lanes, respectively. After adding one lane, the roadway B4-C5 became a 5-lane eastbound road, and E5-F5 became a 4-lane eastbound road. Besides, all the signalizations of ring barrier-controlled intersections are updated accordingly. All the left and right turns are also adjusted with adjacent roadways.

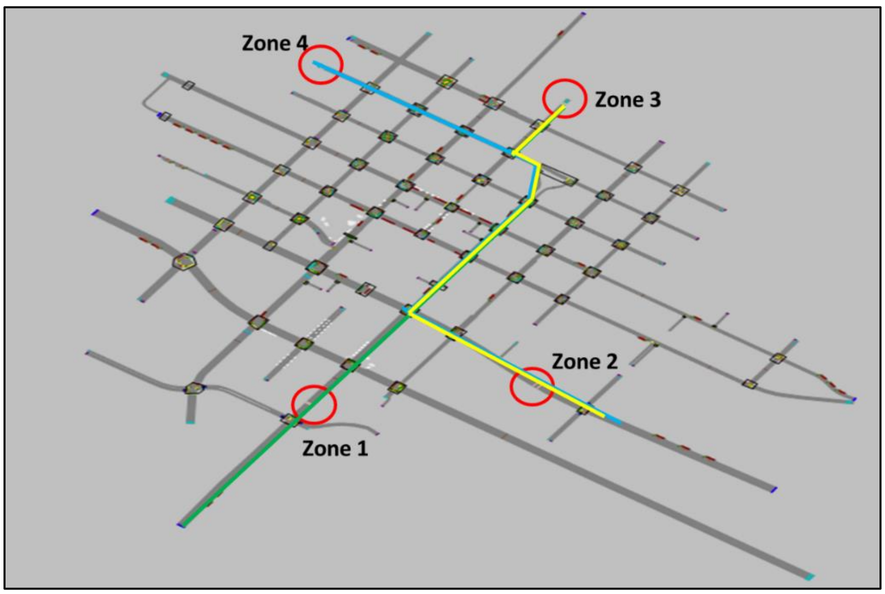


Figure 23: Boise Downtown Road Network (Zones)

The average travel time and vehicle delay for all the four OD pairs are obtained from the simulation results. Then, the weighted average (by volume) travel time for vehicles traveling from zone 1 to zone 3 and zone 4 is calculated using the following equation-

$$TT_{1\text{-}3,4} = \frac{(TT1{,}3 \times V1{,}3)+(TT1{,}4 \times V1{,}4)}{(V1{,}3+V1{,}4)} \tag{6}$$

Here,

$TT_{1-3,4}$ = Weighted average (by volume) travel time of vehicles from zone 1 to zone 3 & 4

$TT_{1,3}$ = Average travel time of vehicles traveling from zone 1 to zone 3

$TT_{1,4}$ = Average travel time of vehicles traveling from zone 1 to zone 4

$V_{1,3}$ = Volume of traffic from zone 1 to zone 3

$V_{1,4}$ = Volume of traffic from zone 1 to zone 4

The weighted average (by volume) travel time for vehicles traveling from zone 2 to zone 3 and zone 4 and for from all to all zones (from zone 1 to zone 3, zone 1 to zone 4, zone 2 to zone 3 and zone 2 to zone 4) are calculated using the same equation 6. The results for all three cases (congested base case, adding one lane to central roadway E5-F5 and other roadway B4-C5) are plotted in Figure 24 (percent change in travel time) and in Figure 25 (percent change in vehicle delay).

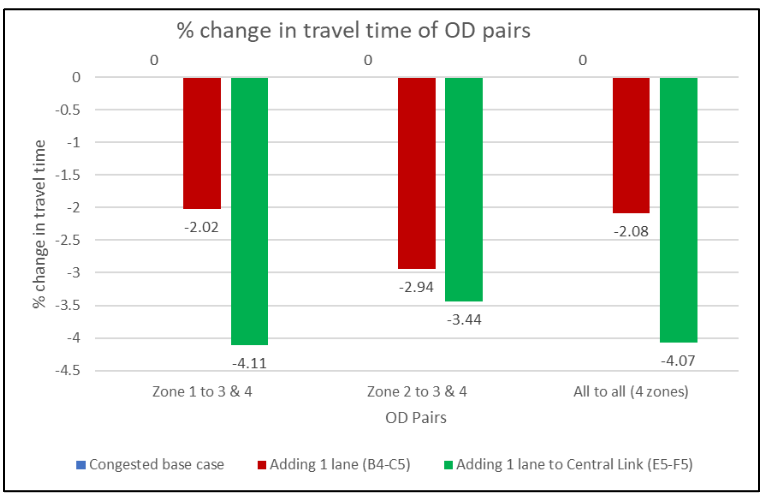


Figure 24: Percent Change in Travel Time for OD Pairs

From Figure 24, it is observed that the percent change in travel times is higher for all the three combinations of OD pairs for central roadway E5-F5 (i.e., 4.1% reduction from zone 1 to zone 2 and 3) compared to the other roadway B4-C5. From Figure 25, Similar results are also observed for the central roadway (i.e., 10.4% reduction from zone 2 to zone

3 and 4) in case of the percent change in vehicle delay. Besides, the level of service (LOS) improved from LOS F to LOS E after adding one lane to the central roadway E5-F5; on the other hand, LOS did not improve for the same intervention implementation on less central roadway B4-C5.

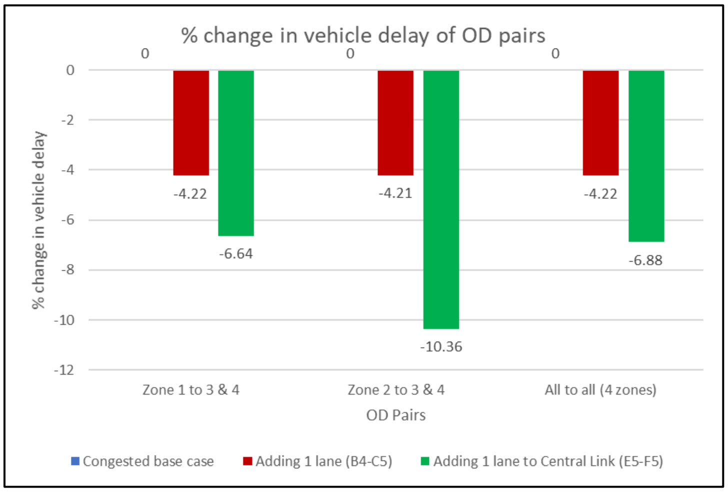


Figure 25: Percent Change in Vehicle Delay for OD Pairs

System Performance Comparison

To compare the system performance of implementing design intervention on both roadway segments, total travel time and total delays are determined from the simulations. Then, the improvement is defined as the reduction in total travel time and total delays (after implementing design intervention) with respect to the base case. In Figure 26, improvement in total travel time (left bar chart) and in total delay (right bar chart) are plotted for both roadways. From the system level, applying intervention on central roadway segment (E5-F5) shows 30% more improvement in travel time as compared to the less central roadway (B4-C5). In case of total vehicle delay, central roadway also shows better improvement which is 70% more with respect to the less central roadway.

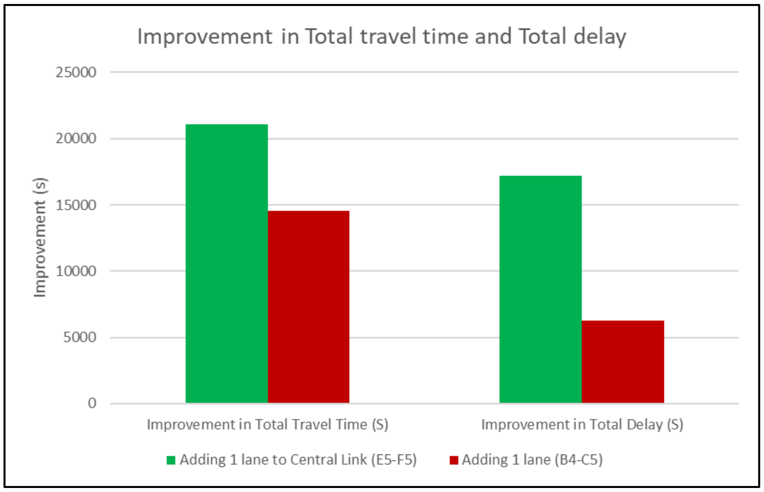


Figure 26: Improvement in Total Travel Time and Total Delay

From all these observations, it showed that implementing intervention on central roadway segments rather than on less central roadways (having similar LOS) improves the system performance better in terms of travel time, vehicle delay and level of service.

4.6 Discussion of Results

This study proposed a strategy for improving road networked system serviceability by implementing interventions on critical components (roadways). The systematic approach combines traditional traffic simulation studies with complex network metrics to improve the serviceability of road networked systems. With a growing attention to risk-based operation and maintenance of transportation systems, an accurate knowledge and importance of the vulnerabilities, as well as consideration of interrelation among intersections and roadways in a network, becomes crucial. Traffic engineers and managers often tend to improve the serviceability of an intersection or a roadway that experiences the worst level of service by implementing different interventions (e.g., signal timing optimization, increasing the roadway capacity and so on) without considering the cascading effects on the surrounding road network. This approach may improve the level of service for a specific intersection or roadway but cannot solve the traffic congestion problem for the surrounding network. When different network components experience similar congestion level, the proposed systematic approach of implementing interventions can be applied, helping traffic engineers and managers decide on the network component alternatives to enhance the system serviceability. Besides, network positions or credentials should be considered along with the level of service while implementing any interventions on network components to improve the roadway serviceability. The contributions and findings of this study are listed below:

- This study systematically applied topological credentials to a real road network (downtown Boise) weighted by real time traffic volume, whereas the existing literature explored unweighted network using other weights (i.e., origin destination demand).
- This research developed an efficient strategy of applying design interventions on critical components (roads) to improve the serviceability of transportation networks, which is not being captured by the empirical literature.
- Lane intervention applied on congested critical roadways increased the level of service from LOS F to LOS E.
- After implementing lane intervention to the critical or central roadway, system travel time improved 35% and total vehicle delay improved 60% as compared to the other roadway experiencing a similar level of service.
- Performance improvements (reduction in weighted average travel time and vehicle delay) for high-demand OD pairs are also observed for lane intervention applied on critical roadways.

The limitation of the analyses is tied with the traffic assignment method, as static traffic assignment is performed here. To improve the serviceability of road network, the application of the research could be further extended in future studies by performing a multiresolution, iterative analysis such as Dynamic Traffic Assignment (DTA). Besides, the intervention (i.e., adding one lane) applied to both roadway segments did not increase the roadway capacity equally, which may influence the results.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The serviceability of transportation networks often gets disrupted due to external events, i.e., natural or man-made. Hence, ensuring the smooth operation of the transportation networks always remains a major concern for both practitioners and researchers. This dissertation is focused on two specific objectives, first to understand how complex network metrics can enhance transportation network resiliency, and second, to develop a systematic approach that improves the serviceability of the transportation network.

To enhance the transportation network resiliency, this dissertation proposed a framework by identifying topological credentials (i.e., rank of relative importance) of physical infrastructure components (roads, bridges), where a combined approach of traditional GIS modeling with network science theories (centrality of bridges) is implemented. The outcome of the proposed approach is a rank of bridges in the road network based on their centrality values (from most central to least central) that can be adopted at different scales, i.e., network size. The study conducted extensive network experiments and demonstrated how such topological credentials can change at different scales. Moreover, these changes are also observed when weights are introduced to the topology (e.g., traffic volumes) to establish relative importance of bridges more in a topological perspective rather than localized ones. This would allow practitioners and other stakeholders performing regular activities to decide which bridge should be inspected, maintained, or constructed first based on the position of the bridges in a network setting.

Different agencies also engage in solving unprecedented problems observed on local roads or bridges; however, this study provides novel insights on how to go beyond local context and incorporate a broader perspective to avoid cascading effects in such networks.

Moreover, this study introduces a systematic recovery process by applying the prioritized bridge ranking method. Scenario analyses (with and without critical bridges) of a sample (Sioux Falls) road-bridge network are performed to quantify the user optimal travel time. Here, static traffic assignment is applied by considering the Frank-Wolfe algorithm and the Bureau of Public Roads (BPR) function, which measured the improvement of the system serviceability (system travel time and cost) and led to the development of the recovery (resilience) schemes of the bridge network. The quantification of system serviceability (in terms of total travel time) helped to decide on the sequential restoration of bridges to recover the system to its full serviceability.

Complex network metrics can also improve the serviceability of transportation networks. Another objective of this dissertation is to develop a systematic approach that improves the road network serviceability by implementing interventions on the critical road network components (roadways). A real road network (downtown Boise) is analyzed in this study by computing network metrics which identified the critical components of the network. To quantify these phenomena, node-level property is measured by closeness centrality and betweenness centrality; the link-level property of the network is evaluated by the edge betweenness centrality.

After that, traffic simulation is performed to quantify the network serviceability in terms of travel time and vehicle delay for high demand OD pairs as well as the level of services. A before and after scenario of applying interventions on different network components are simulated to find the effectiveness of the proposed strategy. The traffic simulation results show that an intervention applied to critical roadway segment of road network improved the level of service from LOS F to LOS E . In addition, reduced travel time and vehicular delay (after applying intervention on critical components) are also observed for high demand OD pairs of the road network. The proposed strategy to improve the serviceability of road networks based on network credentials will help traffic managers and practitioners decide on which roadways (having a similar level of service) lane interventions should be implemented, as well as establish an efficient plan to enhance transportation system efficiency.

5.2 Research Contributions

The contribution of this research to existing literature and civil engineering are listed below:

- Developed novel approach to unify network science principles and infrastructure resiliency to achieve the network resiliency at different scales of real networks (e.g., transportation network).
- The research also developed data-driven methods to prioritize critical infrastructure components, i.e., roads, bridges, which can help managers and policy makers for developing an efficient plan for transportation infrastructure operation, maintenance and construction works to enhance network resiliency.
- The findings showed that the same network components carry different level of importance at different scales of the network.
- Network experiment showed that the efficient recovery schemes changed at different scales.

- Larger network ensured a more resilient system than the smaller network.
- Developed an effective methodology to recover (resilience) from external shocks by sequential restoration of critical components (roads, bridges).
- Identified a systematic strategy to apply design interventions on critical components (roads) to improve the serviceability of transportation networks.

5.3 Recommendations for Future Research

For enhancing transportation infrastructure network resiliency, the applications of this research can be extended towards any emergency evacuation scenarios by ensuring more efficient route guidance to evacuees and avoiding possible gridlocks due to extreme situations. For example, people in Miami Beach tend to take Venetian and MacArthur Causeways as they evacuate inland, and such preferences can be diverted ahead of time if the vulnerability of the bridges is assessed earlier to ensure more serviceable system. For future studies, a larger road network (e.g., united states) could be considered which may capture a more diverse scaling effect at the state or multi-state level. Previous studies showed how to prioritize infrastructure components (bridges) based on mixed-integer programming (Alipour et al. 2018b); however, the network variables introduced in this study can add to such formulations to deduce more efficient solutions. This study can be extended in future research by many ways, and the specific recommendations are listed below:

- This research is focused on link-level analyses of the road network where topological credentials of bridges are identified and the link attribute (i.e., traffic volume) of the network is considered as weight. Future studies can focus on node-level (i.e., intersections, roundabouts) properties and attributes (i.e., signal timing) as weight of the road networks.

- This study experimented with network analyses considering traffic volume, as a weight of the road network. Future research may consider other relevant factors as link weights (e.g., travel time, vehicle delay, roadway width and so on) to conduct similar analyses.
- This study identified the critical components of the network before simulating the disruption, as the focus was to develop effective recovery schemes of the network components. Identification of critical components after simulating disruption can help to develop strategies for improving performance of the network with irrecoverable components. Future studies may consider identifying critical components of the network (i.e., consisting irrecoverable components) after simulating the disruption and implement design interventions on critical components to improve the performance of the network.
- The study developed systematic recovery schemes of infrastructure components for road network. Future research may apply similar methodology for construction, operation, and maintenance of infrastructure components, which may help managers to take strategic investment decisions for transportation infrastructure.
- To improve the serviceability of transportation network, the application of the research could be further extended in the future by performing a multiresolution, iterative analysis such as Dynamic Traffic Assignment (DTA) to capture the serviceability at network-level through simulation of traffic network.

- New design interventions may also be considered such as adding two critical intersections with a new roadway, diverting traffic to critical intersections/roadways and so on.
- This study showed improvement in road network serviceability by applying intervention on critical components for day-to-day congestion scenario. Future studies may consider applying a similar methodology for disruptions due to extreme events (i.e., hurricane, flood, wildfire).

5.4 Limitation of the Research

Resilience is defined by the four basic properties which are, robustness, rapidity, redundancy, and resourcefulness. Redundancy is defined as the extent to which elements and components (i.e., roads, bridges) of the investigated system (i.e., transportation networks) are substitutable. To achieve robustness (ability to withstand any external shock) and rapidity (ability to recover from any disruption) of transportation network; redundancy (i.e., alternate route), and resourcefulness (i.e., additional money, manpower, materials) of infrastructure components (i.e., roads, bridges) can play a vital role.

In this dissertation, Sioux Falls road network (with hypothetical bridges) is experimented to explain the proposed methodology of enhancing resiliency (in terms of robustness and rapidity) of transportation system. In this network, none of the disrupted road segments (with bridges) had substitutable route (i.e., parallel nearby alternate route) by which vehicles can take re-route to the specific destination without incurring delay. Hence, the effect of redundancy along with robustness and rapidity was not possible to capture in this dissertation. To examine the effect of redundancy, a network with substitutable parallel routes for disrupted roads/bridges are suggested to consider in future research.

The scenario analyses for enhancing transportation network resiliency are conducted for a sample road-bridge network (Sioux Falls) in this research. The conclusion from this analysis would be more credible if the same analysis were conducted for the experimented (i.e., Florida road-bridge) transportation network. Besides, only the effect of existing/internal OD pairs for the smaller scales of the network is captured here. In future research, the effects of external OD pairs can be tested and compared with the effect of existing/internal OD pairs. In case of improving the serviceability of transportation network, the limitation is tied with the network analysis which is conducted only for one scale (Boise downtown) of the network. As network credentials change at different scales (i.e., city, county, state level) of network, future studies may take consideration on this also.

Some practical field experiments can be conducted in future research to validate the dissertation's findings, specifically the impact of inaccessibility of a roadway or bridge. For example, a roadway segment can be made inaccessible to neighboring traffic (i.e., using barricades) with the help of local agencies. As the vehicles traveling through that road segment must take another route, the change in travel time of vehicles from specific origin to destination can be calculated and compared with the regular travel time (i.e., when the roadway is accessible). Then, the difference of these two-travel time can quantify the disruption, which will help to validate the change in travel time observed from the simulation.

The network configuration and demands such as the availability of alternative routes in different parts of the network, congestion level, and OD demand distribution impact the results of the analysis. In this dissertation, the effect of network configuration is described for a smaller scale of the transportation network. To capture the impact of OD demand distribution, availability of alternative routes and congestion level, dynamic traffic assignment (DTA) needs to be performed in future research.

APPENDIX

Table 5: Closeness Centrality (CC) Values for Key-West Road-bridge Network

Bridge Rank	Node Long.	Node Lat.	Closeness Centrality	Roads/Bridges
1	-81.228329	24.6823346	0.118102797	Overseas Hwy
2	-81.1246718	24.7068776	0.113471314	Overseas Hwy
3	-81.6725094	24.5901406	0.107832988	Overseas Hwy
4	-80.958729	24.756647	0.100353243	Overseas Hwy
5	-81.6743332	24.589813	0.099206349	Overseas Hwy
6	-81.047453	24.725695	0.099206349	Overseas Hwy
7	-80.9235268	24.777144	0.092840166	Overseas Hwy
8	-81.7427334	24.5729766	0.091857731	Overseas Hwy
9	-81.047491	24.725827	0.089031339	Overseas Hwy
10	-81.752044	24.5699624	0.088127468	Overseas Hwy
11	-80.91951	24.7785898	0.085522715	Overseas Hwy
12	-81.7432766	24.5728014	0.085522715	Overseas Hwy
13	-81.7434696	24.5726258	0.082280147	Overseas Hwy
14	-80.640942	24.9131724	0.078557064	Overseas Hwy
15	-81.742596	24.572912	0.077160494	Overseas Hwy
16	-81.6736356	24.5897558	0.072640632	Overseas Hwy
17	-81.6733966	24.5897918	0.068620993	Overseas Hwy
18	-80.374722	25.1707516	0.037037037	Overseas Hwy
19	-80.3742914	25.17166	0.027777778	Overseas Hwy

Table 6: Edge Betweenness Centrality (EBC) Values for Key-West Road-bridge Network

Bridge Rank	Start Long.	Start Lat.	End Long.	End Lat.	EBC	Roads/Bridges
1	-81.6734	24.58979	-81.2283	24.68233	0.217717718	Ovrs Hwy
2	-81.6736	24.58976	-81.6734	24.58979	0.216216216	Ovrs Hwy
3	-81.7426	24.57291	-81.6736	24.58976	0.214714715	Ovrs Hwy
4	-81.7435	24.57263	-81.7426	24.57291	0.213213213	Ovrs Hwy
5	-81.752	24.56996	-81.7435	24.57263	0.211711712	Ovrs Hwy
6	-81.7433	24.5728	-81.7522	24.57011	0.201201201	Ovrs Hwy
7	-81.7427	24.57298	-81.7433	24.5728	0.1996997	Ovrs Hwy
8	-81.6743	24.58981	-81.7427	24.57298	0.198198198	Ovrs Hwy
9	-81.6725	24.59014	-81.6743	24.58981	0.196696697	Ovrs Hwy
10	-81.2283	24.68233	-81.6725	24.59014	0.195195195	Ovrs Hwy
11	-81.0475	24.7257	-80.9587	24.75665	0.154654655	Ovrs Hwy
12	-81.1247	24.70688	-81.0475	24.7257	0.153153153	Ovrs Hwy
13	-81.2283	24.68233	-81.1247	24.70688	0.144144144	Ovrs Hwy
14	-81.0475	24.72583	-81.1247	24.70688	0.127627628	Ovrs Hwy
15	-80.9587	24.75665	-81.0475	24.72583	0.126126126	Ovrs Hwy
16	-80.9587	24.75665	-80.9235	24.77714	0.12012012	Ovrs Hwy
17	-81.1247	24.70688	-81.2283	24.68233	0.12012012	Ovrs Hwy
18	-80.9235	24.77714	-80.9195	24.77859	0.11036036	Ovrs Hwy
19	-80.9195	24.77859	-80.6409	24.91317	0.099099099	Ovrs Hwy
20	-80.6409	24.91317	-80.3748	25.17029	0.097597598	Ovrs Hwy
21	-80.9235	24.77714	-80.9587	24.75665	0.09009009	Ovrs Hwy
22	-80.9195	24.77859	-80.9235	24.77714	0.078828829	Ovrs Hwy
23	-80.6409	24.91317	-80.9195	24.77859	0.066066066	Ovrs Hwy
24	-80.3747	25.17075	-80.6409	24.91317	0.063063063	Ovrs Hwy
25	-80.3743	25.17166	-80.3747	25.17075	0.043543544	Ovrs Hwy

Table 7: Closeness Centrality (CC) Values for Miami-Dade Road-bridge Network

Bridge Rank	Node Long.	Node Lat.	Closeness Centrality	Roads/Bridges
1	-80.2637	25.7717	0.015244	W Flagler St
2	-80.2392	25.7723	0.014857	W Flagler St
3	-80.2735	25.7340	0.014087	Granada Blvd
4	-80.2727	25.8082	0.014011	East Dr
5	-80.2897	25.7043	0.013923	Sunset Dr
6	-80.2727	25.8081	0.013721	East Dr
7	-80.2899	25.7042	0.013622	Sunset Dr
8	-80.1886	25.7795	0.012464	Biscayne Blvd
9	-80.1893	25.7820	0.012332	Biscayne Blvd
10	-80.1889	25.7801	0.012222	Biscayne Blvd
11	-80.1893	25.7839	0.012096	Biscayne Blvd
12	-80.1892	25.7801	0.011950	Biscayne Blvd
13	-80.1891	25.7853	0.011868	Biscayne Blvd
14	-80.1889	25.7792	0.011735	Biscayne Blvd
15	-80.1890	25.7861	0.011649	Biscayne Blvd
16	-80.1891	25.7870	0.011632	Biscayne Blvd
17	-80.1891	25.7883	0.011492	Biscayne Blvd
18	-80.1890	25.7861	0.011438	Biscayne Blvd
19	-80.1891	25.7861	0.011421	Biscayne Blvd
20	-80.1891	25.7896	0.011355	Biscayne Blvd

Table 8: Edge Betweenness Centrality (EBC) Values for Miami-Dade Road-bridge Network

Unweighted Rank	Weighted Rank	Start Long.	Start Lat.	End Long.	End Lat.	Weight (AADT)	Unweighted EBC	Weighted EBC	Roads/Bridges
1	1	-80.1889	25.7801	-80.1893	25.7820	37297	0.079154	0.068973	Bscn Blvd
2	2	-80.1886	25.7795	-80.1889	25.7801	26070	0.079150	0.068970	Bscn Blvd
3	3	-80.1890	25.7861	-80.1891	25.7870	35988	0.077585	0.067270	Bscn Blvd
4	4	-80.1890	25.7861	-80.1890	25.7861	37500	0.077581	0.067268	Bscn Blvd
5	5	-80.1891	25.7853	-80.1890	25.7861	37500	0.077577	0.067265	Bscn Blvd
6	6	-80.1893	25.7839	-80.1891	25.7853	37930	0.077572	0.067262	Bscn Blvd
7	7	-80.1893	25.7820	-80.1893	25.7839	38000	0.077568	0.067260	Bscn Blvd
8	8	-80.1891	25.7870	-80.1891	25.7883	33500	0.075370	0.064964	Bscn Blvd
9	9	-80.1891	25.7883	-80.1891	25.7896	33500	0.075184	0.064762	Bscn Blvd
10	**19**	**-80.1220**	**25.9299**	**-80.1219**	**25.9304**	**54000**	**0.075149**	**0.062392**	**Clns Ave**
11	10	-80.1891	25.7896	-80.1890	25.7962	33500	0.074997	0.064560	Bscn Blvd
12	11	-80.1890	25.7962	-80.1894	25.8043	36018	0.074809	0.064358	Bscn Blvd
13	12	-80.1894	25.8043	-80.1894	25.8107	33067	0.074621	0.064155	Bscn Blvd
14	13	-80.1894	25.8107	-80.1894	25.8114	42500	0.074441	0.063951	Bscn Blvd
15	14	-80.1894	25.8114	-80.1894	25.8116	42500	0.074260	0.063747	Bscn Blvd

16	15	-80.1894	25.8116	-80.1893	25.8124	118000	0.074078	0.063543	Bscn Blvd
17	16	-80.1891	25.8134	-80.1869	25.8255	35768	0.074037	0.063459	Bscn Blvd
18	17	-80.1893	25.8124	-80.1891	25.8134	35500	0.074032	0.063457	Bscn Blvd
19	18	-80.1840	25.8327	-80.1841	25.8333	40000	0.073301	0.062631	Bscn Blvd
20	**22**	**-80.1227**	**25.8871**	**-80.1220**	**25.9299**	**49883**	**0.073270**	**0.060786**	**Clns Ave**
21	20	-80.1841	25.8333	-80.1841	25.8334	40000	0.072607	0.061886	Bscn Blvd
22	21	-80.1841	25.8334	-80.1846	25.8478	40000	0.072421	0.061677	Bscn Blvd
23	**51**	**-80.1539**	**25.9262**	**-80.1559**	**25.9262**	**51500**	**0.049956**	**0.034025**	**Bscn Blvd**
24	**57**	**-80.2637**	**25.7717**	**-80.2634**	**25.7644**	**44000**	**0.048500**	**0.026107**	**W Flglr St**
25	24	-80.1889	25.7792	-80.1878	25.7753	36000	0.046977	0.048211	Bscn Blvd
26	45	-80.2897	25.7043	-80.2899	25.7042	41786	0.046962	0.036088	Sunset Dr
27	26	-80.1892	25.7801	-80.1889	25.7792	26493	0.045677	0.046896	Bscn Blvd
28	27	-80.1896	25.7839	-80.1895	25.7820	38000	0.044392	0.045498	Bscn Blvd
29	28	-80.1893	25.7855	-80.1896	25.7839	37900	0.044388	0.045495	Bscn Blvd
30	29	-80.1892	25.7860	-80.1893	25.7855	37500	0.044384	0.045492	Bscn Blvd
31	30	-80.1891	25.7861	-80.1892	25.7860	37500	0.044379	0.045490	Bscn Blvd
32	31	-80.1891	25.7870	-80.1891	25.7861	33500	0.044375	0.064964	Bscn Blvd
33	52	-80.2899	25.7042	-80.2909	25.7034	73000	0.044199	0.033205	Sunset Dr

34	32	-80.1891	25.7883	-80.1891	25.7870	33500	0.042155	0.064762	Bscn Blvd
35	33	-80.1891	25.7896	-80.1891	25.7883	33500	0.041964	0.064560	Bscn Blvd
36	34	-80.1890	25.7962	-80.1891	25.7896	36018	0.041773	0.064358	Bscn Blvd
37	35	-80.1894	25.8043	-80.1890	25.7962	33067	0.041581	0.064155	Bscn Blvd
38	36	-80.1894	25.8107	-80.1894	25.8043	42500	0.041388	0.063951	Bscn Blvd
39	37	-80.1894	25.8114	-80.1894	25.8107	42500	0.041203	0.063747	Bscn Blvd
40	38	-80.1894	25.8116	-80.1894	25.8114	118000	0.041018	0.063543	Bscn Blvd
41	39	-80.1893	25.8124	-80.1894	25.8116	35500	0.040832	0.063457	Bscn Blvd
42	40	-80.1892	25.8134	-80.1893	25.8124	35500	0.040782	0.041649	Bscn Blvd
43	41	-80.1841	25.8327	-80.1870	25.8255	40000	0.040029	0.040811	Bscn Blvd
44	42	-80.1841	25.8333	-80.1841	25.8327	40000	0.040024	0.061886	Bscn Blvd
45	43	-80.1841	25.8334	-80.1841	25.8333	40000	0.039326	0.061677	Bscn Blvd
46	**23**	**-80.3684**	**25.5797**	**-80.3664**	**25.5818**	**53500**	**0.036177**	**0.048487**	**Carbn Blvd**
47	**25**	**-80.3595**	**25.5890**	**-80.3541**	**25.5986**	**53500**	**0.035879**	**0.048175**	**Marlin Rd**
48	**44**	**-80.2392**	**25.7723**	**-80.2389**	**25.7652**	**38000**	**0.030916**	**0.039768**	**W Flagler St**
49	**46**	**-80.1234**	**25.8160**	**-80.1211**	**25.8420**	**42904**	**0.027048**	**0.036087**	**Clns Ave**
50	**47**	**-80.1229**	**25.8138**	**-80.1234**	**25.8160**	**15000**	**0.027043**	**0.036084**	**Clns Ave**

*Unweighted road-bridge network is considered as the base network for comparison

Table 9: Closeness Centrality (CC) Values of Florida Road-bridge Network

Bridge Rank	Node Long.	Node Lat.	Closeness Centrality	Roads/Bridges
1	-80.8036	27.6697	0.006676	State Road 60
2	-80.6435	27.6402	0.006616	State Road 60
3	-81.8435	27.9045	0.006615	Van Fleet Dr
4	-81.9575	28.0550	0.006588	N Florida Ave
5	-81.9407	28.0441	0.006564	E Main St
6	-81.9409	28.0441	0.006561	E Main St
7	-80.6435	27.6405	0.006557	State Road 60
8	-81.9573	28.0555	0.006535	N Florida Ave
9	-81.9469	28.0441	0.006532	E Main St
10	-81.9573	28.0548	0.006532	N Florida Ave
11	-81.9575	28.0548	0.006532	N Florida Ave
12	-81.9703	28.0549	0.006532	Kathleen Rd
13	-82.1703	28.5078	0.006517	Treiman Blvd
14	-80.8034	27.6699	0.006497	State Road 60
15	-82.1953	28.5079	0.006487	Cortez Blvd
16	-81.9574	28.0497	0.006473	George Jenkins Blvd
17	-81.9705	28.0549	0.006473	Kathleen Rd
18	-82.204	28.3649	0.006469	Meridian Ave
19	-82.1931	28.5079	0.006469	Cortez Blvd
20	-81.9412	28.0550	0.006462	E Memorial Blvd

Table 10: Edge Betweenness Centrality (EBC) Values of Florida Road-bridge Network

Unweighted Rank	Weighted Rank	Start Long.	Start Lat.	End Long.	End Lat.	Weight (AADT)	Unweighted EBC	Weighted EBC	Roads/Bridges
1	1	-81.3583	27.2972	-81.3626	27.3174	17800	0.0612181	0.0855220	US-27 S
2	**294**	**-81.9412**	**28.0550**	**-81.9569**	**28.0550**	**35888**	**0.0592377**	**0.0099064**	**E Mmrl Blvd**
3	**93**	**-81.8435**	**27.9045**	**-81.8433**	**27.9040**	**38000**	**0.0553112**	**0.0311746**	**Van Fleet Dr**
4	2	-81.9573	28.0556	-81.9573	28.0624	35000	0.0550132	0.0838625	N Florida Ave
5	**452**	**-81.9569**	**28.0550**	**-81.9573**	**28.0556**	**24500**	**0.0537450**	**0.0050895**	**Mmrl Blvd**
6	**1078**	**-81.9407**	**28.0442**	**-81.9408**	**28.0546**	**12800**	**0.0521861**	**0.0016348**	**E Main St**
7	**67**	**-81.9573**	**28.0549**	**-81.9412**	**28.0549**	**34253**	**0.0498294**	**0.0787735**	**N Florida Ave**
8	**80**	**-81.9575**	**28.0550**	**-81.9573**	**28.0549**	**24500**	**0.0478417**	**0.0446420**	**N Florida Ave**
9	**94**	**-81.9409**	**28.0442**	**-81.9408**	**28.0385**	**12800**	**0.0462698**	**0.0310316**	**E Main St**
10	6	-81.9574	28.0624	-81.9575	28.0550	35000	0.0451576	0.0737822	N Florida Ave
11	**427**	**-81.8014**	**27.7520**	**-81.8215**	**27.8202**	**16000**	**0.0393595**	**0.0059624**	**US-17 N**
12	**428**	**-81.8215**	**27.8202**	**-81.8216**	**27.8209**	**16000**	**0.0393594**	**0.0059619**	**US-17 N**
13	36	-84.3875	30.0843	-84.3806	30.1042	8700	0.0367902	0.0456869	Coastal Hwy
14	55	-81.5145	27.5955	-81.4952	27.5148	30000	0.0353305	0.0425612	W Main St
15	12	-84.3804	30.1047	-84.3875	30.0843	8700	0.0349743	0.0601352	Coastal Hwy

16	20	-80.4400	26.1369	-80.4423	26.1473	10810	0.0342811	0.0515896	US-27 N
17	56	-81.3585	27.2972	-81.3585	27.2971	17800	0.0341818	0.0855220	US-27 S
18	10	-81.4174	26.4185	-81.4093	26.4180	6952	0.0335133	0.0623579	E Main St
19	11	-81.4093	26.4180	-81.4089	26.4179	6700	0.0335132	0.0623575	E Main St
20	57	-82.0455	28.8471	-82.0455	28.8387	14000	0.0329285	0.0418747	S Main St
21	58	-82.0455	28.8387	-82.0455	28.8361	12197	0.0329284	0.0418743	S Main St
22	40	-82.6120	28.9231	-82.6267	28.9526	16900	0.0327100	0.0446017	N Suncoast Blvd
23	41	-82.6267	28.9526	-82.6352	28.9696	16900	0.0327099	0.0446013	N Suncoast Blvd
24	42	-82.6352	28.9696	-82.6354	28.9700	16900	0.0327098	0.0446008	N Suncoast Blvd
25	43	-82.6354	28.9700	-82.6691	29.0304	8616	0.0327096	0.0446004	N Suncoast Blvd
26	21	-82.1953	28.5078	-82.1704	28.5078	16500	0.0327087	0.0563814	Cortez Blvd
27	22	-82.2381	28.5231	-82.2358	28.5231	16820	0.0326741	0.0511735	Cortez Blvd
28	23	-82.2358	28.5231	-82.1975	28.5078	16500	0.0326277	0.0511253	Cortez Blvd
29	**3225**	**-82.1975**	**28.5078**	**-82.1953**	**28.5078**	**16500**	**0.0326275**	**0.0563814**	**Cortez Blvd**
30	24	-82.3671	28.5428	-82.3031	28.5231	19100	0.0324811	0.0508994	Cortez Blvd
31	45	-82.8232	29.4170	-82.8596	29.4748	3400	0.0320685	0.0440034	S Main St
32	46	-82.8596	29.4748	-82.8600	29.4876	9153	0.0320684	0.0440030	S Main St
33	59	-82.0430	28.8583	-82.0455	28.8476	18144	0.0318837	0.0397539	S Main St

34	60	-82.0455	28.8476	-82.0455	28.8471	14000	0.0318836	0.0397535	S Main St
35	69	-80.5827	27.0963	-80.6773	27.1590	7100	0.0314177	0.0501940	SW Wrfld Blvd
36	70	-80.4824	27.0305	-80.5827	27.0963	10847	0.0313885	0.0501645	SW Wrfld Blvd
37	71	-80.4468	27.0065	-80.4495	27.0085	10900	0.0313709	0.0500852	SW Wrfld Blvd
38	72	-80.4495	27.0085	-80.4824	27.0305	10842	0.0313708	0.0346999	SW Wrfld Blvd
39	**503**	**-82.4037**	**28.5402**	**-82.3691**	**28.5422**	**22132**	**0.0305668**	**0.0043342**	**Cortez Blvd**
40	**504**	**-82.3691**	**28.5422**	**-82.3671**	**28.5428**	**19356**	**0.0305667**	**0.0043338**	**Cortez Blvd**
41	**3247**	**-81.5145**	**27.5956**	**-81.5145**	**27.5955**	**9500**	**0.0302646**	**0.0321860**	**W Main St**
42	14	-82.1953	28.5080	-82.2359	28.5232	16500	0.0301505	0.0577123	Cortez Blvd
43	**3235**	**-82.2359**	**28.5232**	**-82.2382**	**28.5232**	**16900**	**0.0301504**	**0.0577119**	**Cortez Blvd**
44	15	-82.2382	28.5232	-82.3031	28.5233	16900	0.0301502	0.0577119	Cortez Blvd
45	73	-84.2156	30.1906	-84.1836	30.1998	3497	0.0300947	0.0337856	Coastal Hwy
46	74	-84.2465	30.1737	-84.2156	30.1906	3497	0.0300550	0.0337449	Coastal Hwy
47	75	-84.3138	30.1409	-84.2465	30.1737	3500	0.0300154	0.0337042	Coastal Hwy
48	47	-82.4207	28.5525	-82.4208	28.5777	13900	0.0300098	0.0437691	W Jefferson St
49	76	-84.3806	30.1042	-84.3801	30.1050	10011	0.0299837	0.0336729	Coastal Hwy
50	77	-84.3801	30.1050	-84.3138	30.1409	4700	0.0299835	0.0336725	Coastal Hwy

*Unweighted road-bridge network is considered as the base network for comparison

Table 11: Scaling Effects Based on Node Property (Unweighted Closeness Centrality) of Network

Node Coordinates		Bridge Rank			Unweighted Closeness Centrality			
Long.	Lat.	Florida	Miami-Dade	Miami Beach	Florida	Miami-Dade	Miami Beach	Roads/Bridges
-80.1220	25.9299	1199	37	1	0.004509	0.009720	0.020644	Collins Ave
-80.1204	25.9538	1252	45	2	0.004460	0.009349	0.019895	Collins Ave
-80.1469	25.9552	1279	56	3	0.004435	0.009043	0.019278	Biscayne Blvd
-80.1202	25.9556	1284	49	4	0.004432	0.009227	0.019172	S Ocean Dr
-80.1207	25.9501	1262	42	5	0.004453	0.009429	0.019137	Collins Ave
-80.1540	25.9260	1144	54	6	0.004563	0.009087	0.019049	Biscayne Blvd
-80.1539	25.9262	1288	51	7	0.004428	0.009170	0.018985	Biscayne Blvd
-80.1469	25.9601	1306	55	8	0.004414	0.009056	0.018747	Biscayne Blvd
-80.1537	25.9260	1172	58	9	0.004534	0.008971	0.018609	Biscayne Blvd
-80.1469	25.9550	1316	61	10	0.004408	0.008915	0.018579	Biscayne Blvd
-80.1193	25.9860	1319	53	11	0.004405	0.009108	0.018501	S Ocean Dr
-80.1423	25.9856	1317	64	12	0.004407	0.008830	0.018413	Federal Hwy
-80.1564	25.9168	1173	59	13	0.004534	0.008958	0.018380	Biscayne Blvd
-80.1847	25.8501	1404	36	14	0.004312	0.009857	0.018343	Biscayne Blvd
-80.1841	25.8334	1427	34	15	0.004281	0.010089	0.018297	Biscayne Blvd

-80.1841	25.8333	1435	32	16	0.004266	0.010192	0.018170	Biscayne Blvd
-80.1535	25.9266	1207	63	17	0.004505	0.008844	0.017965	Biscayne Blvd
-80.1468	25.9497	1348	65	18	0.004380	0.008790	0.017937	Biscayne Blvd
-80.1508	25.9347	1220	67	19	0.004492	0.008729	0.017911	Biscayne Blvd
-80.1849	25.8562	1424	39	20	0.004286	0.009706	0.017737	Biscayne Blvd

* Miami Beach road-bridge network is considered as the base network for comparison

Table 12: Scaling Effects Based on Link Property (Unweighted Edge Betweenness Centrality) of Network

Link Coordinates				Bridge Rank			Unweighted Edge Betweenness Centrality			
Start Long	Start Lat	End Long	End Lat	Florida	Miami-Dade	Miami Beach	Florida	Miami-Dade	Miami Beach	Roads/Bridges
-80.1220	25.9299	-80.1219	25.9304	258	10	1	0.01022	0.07515	0.08365	Collins Ave
-80.1227	25.8871	-80.1220	25.9299	355	20	2	0.00747	0.07327	0.07132	Collins Ave
-80.1840	25.8327	-80.1841	25.8333	494	19	3	0.00412	0.07330	0.06068	Biscayne Blvd
-80.1841	25.8334	-80.1846	25.8478	491	22	4	0.00418	0.07242	0.06039	Biscayne Blvd
-80.1841	25.8333	-80.1841	25.8334	493	21	5	0.00414	0.07261	0.06026	Biscayne Blvd
-80.1893	25.8124	-80.1891	25.8134	502	18	6	0.00400	0.07403	0.06015	Biscayne Blvd

-80.1891	25.8134	-80.1869	25.8255	503	17	7	0.00400	0.07404	0.06009	Biscayne Blvd
-80.1893	25.7820	-80.1893	25.7839	497	7	8	0.00406	0.07757	0.05974	Biscayne Blvd
-80.1893	25.7839	-80.1891	25.7853	498	6	9	0.00406	0.07757	0.05968	Biscayne Blvd
-80.1891	25.7853	-80.1890	25.7861	499	5	10	0.00406	0.07758	0.05962	Biscayne Blvd
-80.1890	25.7861	-80.1890	25.7861	500	4	11	0.00406	0.07758	0.05956	Biscayne Blvd
-80.1890	25.7861	-80.1891	25.7870	501	3	12	0.00406	0.07759	0.05950	Biscayne Blvd
-80.1894	25.8116	-80.1893	25.8124	520	16	13	0.00390	0.07408	0.05908	Biscayne Blvd
-80.1894	25.8114	-80.1894	25.8116	523	15	14	0.00387	0.07426	0.05891	Biscayne Blvd
-80.1894	25.8107	-80.1894	25.8114	531	14	15	0.00386	0.07444	0.05874	Biscayne Blvd
-80.1894	25.8043	-80.1894	25.8107	533	13	16	0.00384	0.07462	0.05856	Biscayne Blvd
-80.1890	25.7962	-80.1894	25.8043	536	12	17	0.00383	0.07481	0.05838	Biscayne Blvd
-80.1891	25.7896	-80.1890	25.7962	539	11	18	0.00382	0.07500	0.05820	Biscayne Blvd
-80.1891	25.7883	-80.1891	25.7896	540	9	19	0.00381	0.07518	0.05801	Biscayne Blvd
-80.1891	25.7870	-80.1891	25.7883	537	8	20	0.00382	0.07537	0.05781	Biscayne Blvd

* Miami Beach road-bridge network is considered as the base network for comparison

Table 13: Link Attributes of Sioux Falls Road-bridge Network

Link id	From node	To node	Distance	Capacity (vehicle per day)	Free flow travel time (minutes)
1	1	2	6	25900.2	6
2	1	3	4	23403.47	4
3	2	1	6	25900.2	6
4	2	6	5	4958.181	5
5	3	1	4	23403.47	4
6	3	4	4	17110.52	4
7	3	12	4	23403.47	4
8	4	3	4	17110.52	4
9	4	5	2	17782.79	2
10	4	11	6	4908.827	6
11	5	4	2	17782.79	2
12	5	6	4	4947.995	4
13	5	9	5	10000	5
14	6	2	5	4958.181	5
15	6	5	4	4947.995	4
16	6	8	2	4898.588	2
17	7	8	3	7841.811	3
18	7	18	2	23403.47	2
19	8	6	2	4898.588	2
20	8	7	3	7841.811	3
21	8	9	10	5050.193	10
22	8	16	5	5045.823	5
23	9	5	5	10000	5
24	9	8	10	5050.193	10

25	9	10	3	13915.79	3
26	10	9	3	13915.79	3
27	10	11	5	10000	5
28	10	15	6	13512	6
29	10	16	4	4854.918	4
30	10	17	8	4993.511	8
31	11	4	6	4908.827	6
32	11	10	5	10000	5
33	11	12	6	4908.827	6
34	11	14	4	4876.508	4
35	12	3	4	23403.47	4
36	12	11	6	4908.827	6
37	12	13	3	25900.2	3
38	13	12	3	25900.2	3
39	13	24	4	5091.256	4
40	14	11	4	4876.508	4
41	14	15	5	5127.526	5
42	14	23	4	4924.791	4
43	15	10	6	13512	6
44	15	14	5	5127.526	5
45	15	19	3	14564.75	3
46	15	22	3	9599.181	3
47	16	8	5	5045.823	5
48	16	10	4	4854.918	4
49	16	17	2	5229.91	2
50	16	18	3	19679.9	3
51	17	10	8	4993.511	8
52	17	16	2	5229.91	2

53	17	19	2	4823.951	2
54	18	7	2	23403.47	2
55	18	16	3	19679.9	3
56	18	20	4	23403.47	4
57	19	15	3	14564.75	3
58	19	17	2	4823.951	2
59	19	20	4	5002.608	4
60	20	18	4	23403.47	4
61	20	19	4	5002.608	4
62	20	21	6	5059.912	6
63	20	22	5	5075.697	5
64	21	20	6	5059.912	6
65	21	22	2	5229.91	2
66	21	24	3	4885.358	3
67	22	15	3	9599.181	3
68	22	20	5	5075.697	5
69	22	21	2	5229.91	2
70	22	23	4	5000	4
71	23	14	4	4924.791	4
72	23	22	4	5000	4
73	23	24	2	5078.508	2
74	24	13	4	5091.256	4
75	24	21	3	4885.358	3
76	24	23	2	5078.508	2

Table 14: Origin-Destination Matrix of Trips for Sioux Falls Road-bridge Network

OD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	100	100	500	200	300	500	800	500	1300	500	200	500	300	500	500	400	100	300	300	100	400	300	100
2	100	0	100	200	100	400	200	400	200	600	200	100	300	100	100	400	200	0	100	100	0	100	0	0
3	100	100	0	200	100	300	100	200	100	300	300	200	100	100	100	200	100	0	0	0	0	100	100	0
4	500	200	200	0	500	400	400	700	700	1200	1400	600	600	500	500	800	500	100	200	300	200	400	500	200
5	200	100	100	500	0	200	200	500	800	1000	500	200	200	100	200	500	200	0	100	100	100	200	100	0
6	300	400	300	400	200	0	400	800	400	800	400	200	200	100	200	900	500	100	200	300	100	200	100	100
7	500	200	100	400	200	400	0	1000	600	1900	500	700	400	200	500	1400	1000	200	400	500	200	500	200	100
8	800	400	200	700	500	800	1000	0	800	1600	800	600	600	400	600	2200	1400	300	700	900	400	500	300	200
9	500	200	100	700	800	400	600	800	0	2800	1400	600	600	600	900	1400	900	200	400	600	300	700	500	200
10	1300	600	300	1200	1000	800	1900	1600	2800	0	4000	2000	1900	2100	4000	4400	3900	700	1800	2500	1200	2600	1800	800
11	500	200	300	1500	500	400	500	800	1400	3900	0	1400	1000	1600	1400	1400	1000	100	400	600	400	1100	1300	600
12	200	100	200	600	200	200	700	600	600	2000	1400	0	1300	700	700	700	600	200	300	400	300	700	700	500
13	500	300	100	600	200	200	400	600	600	1900	1000	1300	0	600	700	600	500	100	300	600	600	1300	800	800
14	300	100	100	500	100	100	200	400	600	2100	1600	700	600	0	1300	700	700	100	300	500	400	1200	1100	400
15	500	100	100	500	200	200	500	600	1000	4000	1400	700	700	1300	0	1200	1500	200	800	1100	800	2600	1000	400
16	500	400	200	800	500	900	1400	2200	1400	4400	1400	700	600	700	1200	0	2800	500	1300	1600	600	1200	500	300
17	400	200	100	500	200	500	1000	1400	900	3900	1000	600	500	700	1500	2800	0	600	1700	1700	600	1700	600	300
18	100	0	0	100	0	100	200	300	200	700	200	200	100	100	200	500	600	0	300	400	100	300	100	0
19	300	100	0	200	100	200	400	700	400	1800	400	300	300	300	800	1300	1700	300	0	1200	400	1200	300	100
20	300	100	0	300	100	300	500	900	600	2500	600	500	600	500	1100	1600	1700	400	1200	0	1200	2400	700	400
21	100	0	0	200	100	100	200	400	300	1200	400	300	600	400	800	600	600	100	400	1200	0	1800	700	500
22	400	100	100	400	200	200	500	500	700	2600	1100	700	1300	1200	2600	1200	1700	300	1200	2400	1800	0	2100	1100
23	300	0	100	500	100	100	200	300	500	1800	1300	700	800	1100	1000	500	600	100	300	700	700	2100	0	700
24	100	0	0	200	0	100	100	200	200	800	600	500	700	400	400	300	300	0	100	400	500	1100	700	0

Table 15: Summary of Impacts of Different Scenarios (Sioux Falls- Small Scale)

Scenarios and Schemes	Modifications in Network	System Travel Time (mins)	% Increase in STT (WRT base case)	Serviceability of Network
Scenario 1	Base case-Fully functional bridge network	175.58	0	100
Scenario 2	Disrupted (3 bridges off) network	286.39	63.11	36.89
Scenario 3	Recovered Network (6 schemes)			
i) Scheme 1	Most central bridge (B1) is active, B2 and B3 are inactive	221.71	26.27	73.73
ii) Scheme 2	Less Central Bridge (B3) is active, B1 and B2 are inactive	262.27	49.37	50.63
iii) Scheme 3	Least Central Bridge (B2) is active, B1 and B3 are inactive	246.31	40.28	59.72
iv) Scheme 4	Most Central Bridge (B1) is inactive, B2 and B3 are active	199.86	13.83	86.17
v) Scheme 5	Less Central Bridge (B3) is inactive, B1 and B2 are active	197.85	12.68	87.32
vi) Scheme 6	Least Central Bridge (B2) is inactive, B1 and B3 are active	180.71	2.92	97.08

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