# Using social network analysis for civil infrastructure management

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It is essential to build, maintain, and use our transportation systems in a manner that meets our current needs while addressing the social and economic needs of future generations. In today's world, transportation congestion causes serious negative impacts to our societies. To this end, researchers have been utilizing various statistical methods to better study the flow of traffic into the road networks. However, these valuable studies cannot realize their true potential without solid in-depth understanding of the connectivity between the various traffic intersections. This paper bridges the gap between the engineering and social science domains. To this end, the authors propose a dynamic social network analysis framework to study the centrality of the existing road networks. This approach utilizes the field of network analysis where: (1) visualization and modeling techniques allow capturing the relationships, interactions, and attributes of and between network constituents, and (2) mathematical measurements facilitate analyzing quantitative relationships within the network. Connectivity and the importance of each intersection within the network will be understood using this method. The author conducted social network analysis modeling using three studies in Louisiana and two studies in Mississippi. Four types of centrality analysis were performed to identify the most central and important intersections within each study area. Results indicate intersection social network analysis modeling aligns with current congestion studies and transportation planning decisions.

# DEDICATION

To my wife Erin, and my children, Autumn, Leah, Faith, and Samuel.  This work is for each of you.

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# CHAPTER I

# INTRODUCTION

## 1.1 Background

Traffic congestion is a common and frequently occurring phenomenon. It is defined as the level at which transportation system performance is unacceptable due to excessive travel times and delays (23 C.F.R. § 500.109). Traffic congestion can be caused by many factors. According to the *Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation* report generated in 2005 by Cambridge Systematics for the FHWA, there are three categories and seven root causes of traffic congestion (Cambridge Systematics 2005). The 2005 report details the categories and causes in the following manner:

- Traffic-Influencing Events (Category 1)

    1. Traffic Incidents – events that disrupt traffic flow;
    2. Work Zones – construction work that physically changes to roadway environment;
    3. Weather – environmental factors that cause drivers to change behavior in a way that alters traffic flow;

- Traffic Demand (Category 2)

    4. Fluctuations in Normal Traffic – variability in day-to-day transportation network demand;
    5. Special Events – demand fluctuations that are drastically different than normal network demand in the area surrounding a special event;

- Physical Highway Features (Category 3)

    6. Traffic Control Devices – traffic control devices such as traffic signals can cause traffic congestion;

    7. Physical Bottlenecks – actual roadway capacity can cause traffic congestion.

The root causes listed above can cause a congested traffic situation at any time. Put simply, traffic congestion is caused by “too much traffic demand and/or not enough supply” (FHWA 2010). It can occur at any time or on any day of the week. It is often assumed that congestion occurs only during traditional morning and afternoon rush hour periods, however, 40 percent of congestion occurs during non-peak travel times (TTI 2011). No matter the time of day that congestion occurs, roadway capacity and travel speeds are reduced, travel time increases and varies and an unstable traffic condition is created (Jun and Lim 2009, Pulugurtha and Pasupuleti 2010). Upon the manifestation of one or more of these indicators, the transportation network is not meeting the needs of its users, causing negative impacts to both individuals and businesses. The 2011 Urban Mobility Report published by the Texas Transportation Institute, highlights the critical cost and time indicators of congestion in 2010 and forecasts these critical indicators for 2020. The indicators, 2010 to 2020 comparisons and forecasted increases are summarized in Table 1.1 below:

Table 1.1 Congestion Indicator Comparison and Forecast

| *Indicators* | *2010* | *2020* | *Forecasted Increase (%)* |
|---|---|---|---|
| Total Cost ($) | 101.0 billion | 175.0 billion | 73.3 |
| Per Commuter Cost ($) | 713.0 | 1232.0 | 72.8 |
| Average Delay Per User (Hours) | 34.0 | 41.0 | 20.6 |
| Total Individual Time Wasted (Hours) | 4.8 billion | 7.7 billion | 60.4 |
| Wasted Fuel (Gallons) | 1.9 billion | 3.2 billion | 68.4 |

Other inauspicious 2010 congestion indicators found in the Texas Transportation Institute's, 2011 Urban Mobility Report, are the following:

- The most congested roadways which account for 21% of travel, were associated with 78% of congestion delays; and
- Since 1982, congestion delay has grown nearly five times larger (TTI 2011).

Major findings detailed in the Texas Transportation Institute's, 2011 Congested Roadways Report, are the following:

- 10% of metropolitan freeway vehicle travel miles are responsible for 36% of metropolitan area freeway delays; and
- 8% of the metropolitan freeway truck miles are responsible for 33% of metropolitan freeway truck delays (TTI 2011).

The following year, the Texas Transportation Institute issued the 2012 Urban Mobility Report. This report is the subsequent report to the 2011 report discussed earlier. The 2012 Urban Mobility Report detailed similar numbers to the 2011 report, noting that congestion parameters have worsened year over year, detailing several major factors that got worse, including, longer trips and less reliable trip times, longer congestion periods, weekend and rural congestion occurrences, greater congestion impacts to personal and industrial traffic, and reduced air quality in regions with high congestion values (TTI 2012).

The costs noted above are driven by congestion related engine emissions, vehicle wear and tear, wasted time and associated fuel consumption costs (Zheng et al. 2010, Antipova and Wilmot 2012, GAO 1989). In general, traffic congestion can have an overall diminishing effect on economic productivity by limiting mobility and reducing traffic safety (Quddus et al. 2010, Zheng et al. 2010).

Individual health can also be negatively impacted by traffic congestion. Traffic congestion has negatively impacted the physical and psychological well-being of commuters (Levy et al, 2012, GAO 1989). Traffic congestion can cause stress and take time away from healthy or needed activities. As such, high levels of congestion are dangerous to the mental and physical health of commuters. In fact, the National Institutes of Health estimates the cost related to health impacts caused by congestion will be $13 billion in 2020 (Levy et al. 2012).

Many commuters and businesses deal with negative cost and health impacts derived from traffic congestion delays on a daily basis. Transportation network users use the same routes and deal with frequent and/or severe congestion on a recurring basis. Once someone is comfortable with a route and able to regularly predict the route travel time, that route becomes the habitual route when traveling to and from a desired destination. It seems counterintuitive to take a consistently congested route to a destination but commuters are known to take travel routes that they are most able to accurately predict the travel time on (Pulugurtha and Nagaswetha 2010). Transportation network users are therefore hesitant to use untested routes within their transportation network because the travel time prediction of a new route can be less reliable than the time prediction of their regular travel route. Developing a tool that users can intuitively understand while accounting for the complex variables related to traffic congestion could increase new route selection and use.

### 1.2 Problem Statement

In today's world, the problem of congestion in our infrastructure transportation systems has been causing serious negative time and cost impacts to our societies. Because of negative time and cost impacts to our societies and the congestion related conditions described above, an innovative traffic congestion mitigation solution is required. Current investment levels have not met our infrastructure needs, requiring an innovative solution (Shrank et al. 2012).

A solution that better utilizes various statistical methods to study the flow of traffic into the road networks for planning and development purposes is required. Many currently used transportation planning systems, like CORSIM, require a wide variety of detailed information and assumptions to predict congestion and evaluate solutions. The effort to complete traditional models can be very time consuming and costs. To this end, a solution that better utilizes the information and tools available to transportation planners and engineers while maximizing the effectiveness of current infrastructure investment levels is needed. However, these traditional studies cannot realize their true potential without solid in-depth understanding of the interrelated connectivity between traffic intersections in resolving transportation congestion problems. Typical traffic mitigation efforts are focused on creating additional capacity, making operational improvements and managing demand (FHWA 2005). Two of the top traffic influencing events noted earlier are traffic incidents and work zones. A model that can quickly incorporate changing data or traffic conditions to develop alternatives to could help mitigate delays as a result of traffic incidents. Work zone congestion leaves more time for decision makers to determine the best layout and schedule to avoid congestion. However, there is usually not enough time or money for agencies or contractors to perform a full traffic analysis with traditional methods to determine the absolute best solution. A tool that requires less time and resources but still develops helpful analytical data for decision makers would be an asset to project managers and potentially reduce congestion.

According to the FHWA (2005), traditional efforts at creating additional capacity are typically focused on highway, transit and freight capacity improvements. Adding capacity typically involves building new infrastructure, modifying existing networks and improving in place infrastructure. Substantial resources and time are associated with capacity additions. Feasibility studies, voter approval, design phases and construction phases are common components of the process to add capacity to the transportation network. Each of these requires time and resources to complete. As such, capacity additions cannot realize their true potential without solid in-depth understanding of the interrelated connectivity between traffic intersections in mitigating transportation congestion problems.

Making operation adjustments is another method commonly used to mitigate traffic congestion. For arterial streets, which is the focus of this research, common improvements include, information systems, geometric improvements, intersection improvements, access management, advanced signal systems, adjustable lane assignments, incident and event management, signal optimization and parking restrictions (FHWA 2005). Operational improvements to mitigate traffic congestion also focus on related freeway management systems to mitigate traffic congestion on highways. Similar operational improvements can be implemented with transit and freight operations to better manage congestion, as well. However, operational management strategies cannot realize their true potential without solid in-depth understanding of the interrelated connectivity between traffic intersections in mitigating transportation congestion problems.

Demand management is the final method in which congestion management efforts are typically focused. Under demand management considers the following strategies when attempting to mitigate traffic congestion: travel alternatives, land use, pricing, HOV, transit and freight (FHWA 2005). Within these strategies, there are numerous options which transportation planners and users may choose to mitigate traffic congestion. Some of the most well-known options are use of alternative work schedules, telecommuting, transit oriented design, HOT lanes, vanpools, carpool parking priority, subsidized fares and freight delivery restrictions (FHWA 2005). While many of these strategies have been implemented in many congested transportation networks and may help slow the increase of congestion, they have not reduced the congestion level experienced by transportation users. As the 2011 Urban Mobility Report notes, congestion levels and costs are actually forecasted to increase between now and 2020, in spite of the implementation of many of the demand management strategies. This is a clear indicator that the current tools are not as effective as they should be. Engineers are spending time and money on tools and solutions that are not improving congestion factors overall. The reason why demand management, operational management or additional capacity strategies cannot realize their true potential is that none of them involves a solid, in-depth, understanding of the interrelated connectivity between traffic intersections in mitigating transportation congestion problems. This research works to round out the required understanding of connectivity between traffic intersections in mitigating transportation congestion problems.

## 1.3 Goals and Objectives

The main goal of this proposal is to gather in depth analytic information which should enable decision makers to effectively and efficiently prioritize and optimize future infrastructure transportation projects. This goal is in alignment with the first step of congestion mitigation guidelines detailed in manual titled, *Guidelines for Operating Congested Traffic Signals*. Specifically, step 1 of these guidelines, requires the prioritization of locations in need of congestion mitigation (Chaudhary et al. 2010). To accomplish this goal, the research has two main objectives detailed below:

1. Study the centrality of the existing road networks using social network analysis. In accomplishing this objective, the research will attempt to utilize four centrality measures. In regards to Bonacich and Eigenvector centrality, how much traffic to neighboring nodes carry and how central are they to the network? Regarding 2 Step Reach centrality, how many different intersections are within to connections of any specific intersection? Finally, in regards to Betweenness centrality, which intersections have the shortest overall path to all other intersections in the network?

2. Study methods and identify additional focus areas which may be included in this research or future studies and developments. These methods and focus areas include, roadway and intersection geometry, signal timing, methods to collect traffic count data, and geographic layout of the transportation network.

## 1.4 Summary

As America's aging infrastructure struggles to meet the minimum safety requirements and current needs of the public, identifying and implementing innovative tools is critical. The aim of this research and the tool developed is to help industry decision makers identify exact locations for the focus of infrastructure improvements. Utilizing social network analysis for transportation networks, the aim is to develop a holistic tool that may be integrated with other social networking studies and tools.

CHAPTER II

LITERATURE REVIEW

## 2.1 Traffic Congestion

This section provides background information on traffic congestion. It will discuss how and why traffic congestion occurs and the effects of congestions occurrences. This section will then discuss the current tools, resources and procedures in use to mitigate traffic congestion. From this information, it will be apparent why a new method that develops an in depth understanding of the interrelated connectivity between traffic intersections is required to mitigate transportation congestion problems.

### 2.1.1 Causes of Traffic Congestion

Traffic congestion is defined as the level at which transportation system performance is unacceptable due to excessive travel times and delays (23 C.F.R. § 500.109). It can be caused by a multitude of issues. However, as noted in Section 1.1, there are seven main causes of congestion. In the 2005 Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation, generated for the FHWA by Cambridge Systematics, the causes are, traffic incidents, work zones, weather, fluctuations in normal traffic, special events, traffic control devices and physical bottlenecks. At times, only one of these congestion causing issues exist. At other times, more than one of these issues may be present within a transportation network. In some instances, one or more issues may cause give rise to another congestion causing issue, potentially compounding the effect of these congestion causing issues. For instance, a work zone may cause a physical bottleneck which results in congestion and traffic delay. Another example could be when a special event causes a fluctuation in normal traffic which results in congestion and traffic delay. There are many more potential combinations of traffic causing issues.

Martchouk et al. goes on to separate some of these traffic causing issues into recurring and nonrecurring groups (2011). Recurrent traffic congestion is caused by traffic control devices, traffic demand fluctuations and inadequate base capacity while nonrecurring congestion is caused by work zones, weather and special events (Martchouk et al. 2011). Martchouk et al. determined that weather is the primary source of nonrecurring traffic congestion (2011).

Simply because one or more of the issues listed above is present within a traffic network does not indicate the presence of traffic congestion. There are a variety of congestion indicators. When one of these indicators is present or observable within a traffic network, traffic congestion and delay are likely present. Potential indicators of congestion occurrence is reduced driving speeds, longer travel times and/or heavy traffic volumes (Jun and Lim 2009). When vehicles are traveling at speeds less than the speed limit, it is an indicator that one of the congestion causing issues listed above is present and causing a congestion event. Depending on the design capacity of the road, heavy traffic volumes may indicate that congestion is present, as well. Longer travel times can also be an indicator that a congestion causing issue is occurring. However, normal travel times may occur when traffic volumes are under capacity, likely reducing travel times.

Adding traffic volume to the network may increase the travel time without actually causing congestion if the network does not reach its capacity volume.

Another indication that a traffic congestion event is occurring is the observance of traffic oscillations. Traffic oscillations, or stop- and-go traffic, occur when repeated decelerations followed by accelerations are observed within the traffic network (Zheng et al. 2010). Traffic oscillations not only indicate that congestion is occurring, but that there is an increased likelihood of a rear-end vehicle crash (Zheng et al. 2010). The presence of stop-and-go traffic not only indicates that a congestion event is occurring, it also gives warning that the probability of a rear-end vehicle crash occurring has increased. This indicates that even if a congestion event cannot be fully mitigated to eliminate its occurrence, mitigation of stop-and-go traffic may result in a safer transportation network. For example, maintaining slow, but more stable and consistent speeds may be an effective measure in mitigating stop-and-go traffic to reduce rear-end crashes within a transportation network.

### 2.1.2 Effects of Traffic Congestion

Upon the presence of one or more of the congestion causing issues or indicators listed above, numerous effects may impact transportation network users. Effects of traffic congestion be present during or after one congestion event and/or may require multiple, repeated occurrences of congestion events to be present. Both acute and chronically occurring congestion events may impact transportation network users. Effects may be related to economic conditions of individuals or society as a whole and may be related to the individual health of transportation network users.

Economically, traffic congestion can have large and drastic costs. Nearly every effect of congestion has some economic cost related factor associated with it. The first effects of congestion will focus on factors where reduced economic productivity and increased cost are the main concerns. Congestion can result in an increase in fuel consumption (Wu et al. 2011). Increased fuel consumption may be created frequent accelerations, idle time in congestion events or extra fuel used to take a longer travel route to bypass a congestion event. Increased fuel consumption also creates a secondary negative effect on the environment. Using more fuel creates more greenhouse gas and uses more of our limited petroleum resources. Congestion also causes increased travel times which waste transportation network user time (Antipova and Wilmot 2012). A major factor in economic productivity is enhanced mobility which is drastically reduced when individual drivers and commercial vehicles experience congestion delays (Quddus et al. 2010). Time individual travelers spend in congestion is unproductive time. This is time that could be spent at a job or in school in efforts to contribute to the overall success of the economy. Congestion delay also increases costs to businesses. Congestion may delay deliveries, cause employees to work longer hours due to increased travel and transportation times, and add new resources to make up for existing resources that are delayed and held up while in transit. All of these issues add to the costs to operate a business and adversely impact the economic productivity of a market.

Many of the economic factors listed above can also have implications on the health of transportation network users. Two studies, one in 1989 and one in 2012, determine that traffic congestion has detrimental effects on physical and psychological health of transportation network users (GAO 1989, Levy et al. 2012). High levels of congestion are dangerous to both the mental and physical safety of commuters. As a result, healthcare costs are associated with congestion events. The Levy et al. article discussed above and published on the National Institutes of Health website estimates the costs related to health impacts caused by fine particulates released in the air because of congestion and other pollution sources will be $13 billion in 2020 (2010). Levy et al. also determined that in many populated regions with high levels of congestions, economic and time costs associated with congestion are nearly equal to the health related costs due to congestion caused fine particulate pollution (2010). A health impact that is difficult to quantify, but caused by congestion events, is a decreased driver comfort (Zheng et al. 2010). Poor driver comfort can negatively both the physical and mental health of transportation network users.

Potentially one of the most critical effects of traffic congestion is travel time reliability. When a congestion event occurs, the roadway capacity is reduced, creating an unstable traffic condition, which then creates travel time variability (Pulugurtha and Pasupuleti 2010). Travel time variability created by congestion events was determined to be the first or second most important consideration for choosing a particular route, meaning transportation network users will use the route in which they can best predict the travel time required to arrive at their destination (Abdelwahab and Abdel-Aty 2001). As such, when faced with congestion many transportation network users will continue to use the same route if it gives them a consistent travel and destination time. When severe congestion on a selected route occurs, it may be wise to travel on an alternate route, however, the literature indicates that transportation network users will likely continue to travel on the severely congested route. This is because users are better able to predict travel time on a consistently used route, even when severely congested, than they can on a less congested alternative route. They can more accurately predict their travel time in severely congested conditions on the regular route than on the uncongested alternative route.

### 2.1.3 Traditional and Current Congestion Mitigation Efforts

As noted in the introduction section of this research, typical traffic mitigation efforts are focused on creating additional capacity, making operational improvements and managing demand (Cambridge Systematics 2005). Within these focuses, there many focus areas and strategies in use to mitigate traffic congestion.

For example, in evaluating the creation of additional transportation network capacity, adding new infrastructure and improving in the in place network are common solutions studied. According to Antipova and Wilmot, a common practice to improve network capacity is to build loop bypasses (2012). While building loop bypasses is a common practice to improve capacity, improving the existing road network can be an effective option for a much smaller price (Antipova and Wilmot 2012). In reviewing alternatives to modify existing networks or build new infrastructure, many impacts and factors, as well as, capacity adding options should be considered. Potential impacts that may be considered are actual capacity added, cost, sustainability, travel time and many more. Potential options that may be considered to add capacity are road widenings, bridges, new roads, mass transit facilities and many more. Only when all alternatives and impacts have been considered, should a capacity addition be implemented, if at all.

Within demand management efforts to mitigate traffic congestion, pricing is one factor to consider. In fact, effective pricing guarantees efficient use of infrastructure

(Gonzalez-Guzman and Robuste 2011). Effective pricing of infrastructure components like toll lanes, mass transit use and parking facilities can influence the public toward efficient use of infrastructure, helping to mitigate congestion. For example, if using mass transit components of a transportation network at a higher capacity will mitigate traffic congestion, pricing is used to encourage the public to use mass transit at higher rates. Tolling passenger vehicles and charging parking facility fees that cost more than mass transit options encourages individual use of available mass transit options.

Operational improvements may focus on many of the areas described in the introduction. An interesting operational improvement strategy is closure of a link to create a buffer or diversion. Individual network users often treat congested network links like closures, naturally diverting when the observed congestion appears to be stable (Chen et al. 2010). Knowing that individuals naturally divert, attempts to develop models for use in directing diversions have been undertaken. One model may be used by individual drivers or government agencies to quantitatively determine if a traffic diversion should be carried out in a specific situation (Wu et al. 2011). In another case, researchers developed a model for use during evacuation management situations that mitigates congestion by balancing the volume of traffic entering and exiting a specific segment of a transportation network through the forced detour some traffic. These models fail to consider the full connectivity of the transportation network, often focusing on freeway congestion mitigation, potentially at the expense of the arterial network and its intended use.

### 2.1.4 Origin Destination Demand

Origin-destination demand is a critical component of the four step transportation analysis. Origin-destination demand is central to the trip distribution and mode split calculations and analyses. For the purposes of this research, origin-destination demand in determining trip distribution will be the focus. During trip distribution, origins and destinations are assigned for each trip. All trips will be assigned an origin-destination pair. Once all assignments are completed, the origin-destination demand matrix may be completed. This origin-destination matrix may be applied in a variety of models. The common models are listed below:

- Uniform Growth Factor Model
- Fratar Model
- Demand Model
- Choice Model (General)
- Gravity Model

These models have strengths and weaknesses. Many are time consuming, require detailed calculations, and various data estimation. These factors can lead to inaccurate or imprecise models. Because no single model is 100% accurate, the potential for error exists in determining origin-destination demands. Policy makers and engineers can use origin-destination demand calculations to determine transportation infrastructure needs, allocate funding and prioritize network changes or improvements. Often, these decisions are made in very dynamic population areas which are subject to potentially large increases or decreases in origin-destination demand. The cost, permanent nature and political ramifications of transportation infrastructure decisions further complicates the origin-destination calculation and analysis. A greater degree of certainty in origin-destination demand analyses is required so that transportation networks can be designed, built and maintained, in a sustainable manner, at capacities that meet these demands.

Origin-destination demands have large impacts on trip distribution and the overall transportation analysis process. They may not provide the full picture of a transportation network though. O-D matrices match one origin and one destination to create a pair, however, there is not much information on what happens between the origin and destination. For example, the actual route taken could vary widely with traffic taking freeway routes, strictly surface streets, a rural route or some combination of the available options. Related to route variability is traffic volume variability. Traffic volume will increase or decrease with the increase or decrease in individual route usage. The accuracy of O-D calculations is affected by two uncertainty causing variables: route selection and traffic volume variability (Chootinan & Chen, 2011). To accurately calculate origin-destination demands, more detailed information is required. It is desirable to more to have more reliable capacity information to either know the exact capacity of the current network and to reliably forecast the capacity of the future network.

As part of this research multiple origin-destination demand studies were review. No matter the focus of the research, each study focused on at least one of the two main categories in the origin-destination demand calculation: route variability and/or traffic volume accuracy. The route variability category will focus on research and literature that discusses route selection and use factors. The traffic volume accuracy category will focus on research and literature that discusses traffic volume determination, accuracy and attempted improvements. The literature will be reviewed, discussing the research and findings, with a summary provided in a table to compare the findings of each set of research findings. A summary of the literature study findings is contained in Table 1, at the end of this section.

One problem or concern in determining origin-destination demand is the actual route a transportation network user takes between their origin and destination. O-D values give an indication of the demand or importance of selected O-D pairs. Traditionally, telephone surveys, census data and roadside surveys have been used in an attempt to determine the actual route transportation network users prefer and actually use (Wang et al. 2013). A problem with these methods is that as soon as the data has been collected, it is old and possibly obsolete.

Recently, cell phone tracking has been used to estimate traffic volumes on selected links or roadways at specific times. This tracking method provides almost real time transportation network user tracking. This phone tracking method can also be used to determine which O-D pairs contribute to traffic volume on a selected link. Researchers can use this method to analyze how the O-D demand and route selection change when different travel/traffic and environmental events occur. One study indicated that close to 60% of traffic on a congested highway route, during rush hour, was local in nature (Wang et al, 2013). This indicates that the majority of the roadway users are "commuters" with the remaining 40% of traffic being intercity, if not, interstate travelers (Wang et al. 2013).

Cell phone tracking has enabled the accurate tracking of route selection and traffic volume of selected routes. The increased, and more detailed, route information afforded by tracking cell phones could be used to by transportation planners to make more exact transportation network improvements and changes.

The length of time it takes to travel between an O-D pair will impact route selection. Routes with the shortest perceived travel time will be used to connect O-D pairs. Perceived route length is based on several route characteristics: physical length of each route, presence of congestion and the amount of actual traffic compared to the route's capacity (Sofer et al. 2013). A route's perceived travel time is equal to its actual travel time when no congestion is present. Once determined, perceived travel time is a major factor in determining system flexibility. Factored with the number of different routes, as well as, the number of independent links available on these different routes, perceived travel time impacts the flexibility of a model (Sofer et al. 2013). Increasing system flexibility, improves travel time reliability (Sofer et al, 2013). While travel time reliability is increased, a network with a high level of flexibility may complicate the determination of route usage and congestion location.

Cost of selected routes between O-D pairs was found to impact commuting volumes and patterns. Upon completion of toll roads, one study found that the new roads experienced relatively low volumes of traffic between communities because of high tolls (McArthur et al. 2013). Another studied reviewed the financial performance of toll road projects in comparison to the social welfare impacts. These researchers found that project builders and financiers experienced higher profits with higher tolls and lower roadway capacities but lower profits or losses with decreased toll amounts and higher roadway capacities (Subprasom and Chen 2007). These studies demonstrate that infrastructure funding is critical to roadway use and connectivity amongst communities.

The higher profits that builders and financiers make when high tolls are implemented are offset by the lack of connectivity and impact to the social welfare of the area communities. Interesting, both of these studies suggested that government agencies either fully finance infrastructure construction or atleast subsidize the work so that projects can be profitable to builders and financiers while creating high capacity roadways which benefit the social welfare of the surrounding communities (McArthur et al. 2013, Subprasom and Chen 2007). Interestingly, one study found that do-nothing alternatives often have the highest social cost impact (Kim and Kim 2006).

Route uncertainty is one of two variables that directly contribute to uncertainty of the O-D calculation. Route uncertainty is caused by multiple solutions because of incomplete nature of the O-D calculation and by errors in traffic counts (Chootinan and Chen 2011). To control this uncertainty, a generalized demand scale model was developed. This model attempts to account for as much route variability as possible through observed link flow constraints, capacity constraints of unused links and path set (Chootinan and Chen 2011). Research found that this demand model was accurate and within the required confidence intervals when applied an actual transportation network (Chootinan and Chen 2011). The generalized demand model reviewed can be used to more accurately identify critical routes and links within a studied network.

Network capacity reliability is critical to transportation network design and use because it can be used by decision makers when managing infrastructure, improving roadways against disaster and providing a flow control implementation indicator (Chen et al. 2013). Capacity reliability is the probability that a network, at a required service level, can meet the traffic volume demand requirements (Chen et al. 2013). Chen et al., defined 7 measures which use traditional links and nodes in calculating network reliability: connectivity reliability, travel time reliability, within budget time reliability, travel demand reduction reliability, travel demand satisfaction reliability, encountered reliability and capacity reliability (2013). Because these measures focus on individual links or nodes within specific modes of transportation, they do not give a good measure of the entire network capacity and reliability.

To determine full network capacity reliability, a reserve capacity model and network capacity models based on the ultimate capacity and practical utility concepts were developed (Chen et al. 2013). These capacity models are defined below:

- Reserve capacity is the largest full network O-D matrix multiplier that be applied without exceeding individual link capacities or required levels of service;
- Ultimate capacity is the maximum volume a system can process without exceeding individual link or zone capacities;
- Practical capacity is the difference between the O-D that a system can handle and the actual O-D demand that is currently occurring (Chen et al. 2013).

The research found that application of the ultimate and practical capacity models enabled a non-uniform O-D growth, allowing for zonal activity allocation analysis, in conjunction with the physical capacity of zonal land use (Chen et al. 2013). These models expand and improve on existing O-D models because non-uniform O-D growth more accurately reflects actual growth and use patterns. As such, network capacity reliability is improved.

Additional literature found that the amount of budget spent on a network influences capacity reliability. Specifically, network capacity reliability is incrementally increased to a maximum as more budget is spent on a network to enhance volume and capacity (Yim et al. 2011). The incremental jumps could occur when smaller links are able to significantly expand capacities through relatively simple changes like lane additions. Once right of way is used up, capacity increases can only occur through more limited options like improved ITS or by slightly modifying network or road layout. As such, when major budget expenditures have been used up on a link within a network, spending more budget, will not improve capacity reliability.

A third study focused on developing a new capacity model that could be used to estimate the throughput of a network so that higher level flow control and demand management can be performed (Yang et al. 2000). This model can be used to forecast how much additional capacity a network could handle using the existing infrastructure, develop public policies to ensure the network is not overloaded and prepare for infrastructure additions or modifications to accommodate additional traffic flows (Yang et al. 2000). Capacity modeling can be a strong transportation planning tool. This is because it can be used to model future flows to develop policies that limit flow growth to remain within the capacity and plan for infrastructure improvements and additions.

Traffic volume accuracy is key to O-D estimation. Accurate traffic volume information enables a better understanding of the route selection between an O-D pair. It has been determined that ITS programs that install detectors at various locations can accurately count and then predict traffic volume and flows (Lam et al. 2002). Research has shown a strong correlation between predicted traffic flows determined by formulas derived from analyzing actual traffic flows and actual traffic flows observed by counting sensors (Lam et al. 2002). Though not as high, there a correlation between predicted and actual travel time (Lam et al. 2002). The ability to reasonably predict traffic volumes and travel times can be used by transportation planning agencies to modify and maintain their infrastructure. Accurate travel times and traffic volumes can also be used to give transportation network users real time information upon which they may react to use the network links that provide for the fastest travel time.

A summary of the O-D related findings contained in the literature review is detailed in the table below. It can be seen that no one study covered all factors and variables.

Table 2.1 Key O-D Demand Finding Summary

| O-D Demand Variable Impacted | Chen et al. | Chootinan & Chen | Lam et al. | Sofer et al. | Wang et al. | Yang et al. | Yim et al. |
|---|---|---|---|---|---|---|---|
| Route Variability | | X | X | X | X | | X |
| Traffic Volume Accuracy | X | | X | X | X | X | X |
| Factors Studied | | | | | | | |
| Capacity Reliability | X | | | X | | X | X |
| Demand | | X | | | X | | |
| Travel Time | | | X | X | X | | |
| Level of Service | | | | | | X | |
| Origins and Destinations of Users | | | | | X | | |
| General Description | Developed reserve, ultimate and practical capacity measurements. | Developed General Demand Model to account for route choice options. | Model to accurately predict link flows and travel times. | Individual perception drives route selection which can impact travel time and capacity flow. | Used cell phones to track origin & destination of transportation network users. | Model to predict how current infrastructure will handle future volumes. | Reliabilty increases with budget spent. Determined probability capacity will not exceed current capacity. |

Canadian researchers studied the impact transport exclusion has on the mobility of network users. Specifically, they looked to determine why O-D demand numbers were what they were. Users would be excluded from transportation if they lacked access to a private vehicle or public transportation, did not have the time required to travel, or experienced unsafe travel routes (McCray and Brais 2007). Specifically, these researchers focused on women transportation network users and why they did or did not travel. They found that women living in low income communities located away from mass transit stations or stops often experienced high levels of transport exclusion, resulting in these women moving around minimally within their communities and rarely venturing outside of their local communities (McCray and Brais 2007). By seeking to understand why the women studied used various parts of a transportation network the researchers attempted to provide more detail to the O-D demand calculation. Whereas traditional O-D demand can only determine the network volumes, these researchers took a step towards identifying why certain areas of a network have high demand or low demand.

Other researchers have also looked at what influences O-D demand. These researchers found that system flexibility through agency ability to add capacity and the ability of network users to utilize different paths, as well as, toll pricing impacted the O-D demand of the network studied (Damnjanovic et al. 2008). Depending on congestion patterns and toll pricing, the O-D demand of a network would change as users attempted to find the most efficient and fast travel routes. The researchers determined that it was best transportation management professionals and agency decision makers to limit initial capacity, adding capacity after signs of building congestion were detected (Damnjanovic et al. 2008)

### 2.1.5 Signal Timing and Intersection Geometry

Two factors that impact the travel time and traffic volume, that are key in determining O-D demand, are signal timing and geometry. Intersection and roadway geometry can impact the decision making of drivers and safety of the roadway. Signal timing can significantly influence the O-D demand through negative travels times and increased congestion.

Intersection and roadway geometry consists of the general layout of the roadway. Grade changes, both vertically and horizontally, are geometric considerations that can negatively impact the roadway users. Skewness and site distances impact intersections. Layout of minor cross streets and shopping center entrances also impact the overall geometry of the adjacent roadways and intersection. Lane configuration is also a geometric factor that influences roadway and intersection design. Further, it was found that typical four way intersections with turning lanes experience more congestion because they are negatively impacted by skewness and downgrade (Sando & Moses 2009). This finding supports grid network roadway systems and 90 degree intersection crossings. The geometry and layout of shopping center access points and minor cross streets also impacts traffic flow.

It has been determined when planners design roadways with no left turn or congested access out of shopping centers or with poorly timed signals at minor cross streets, roadway users may opt to take right turns, followed by u-turns in an effort to minimize their wait time and travel time (Liu et al. 2007). Liu et al. also found turning right, then making a u-turn to avoid delayed left turns on congested roadways is a common practice used by drivers (2007). Drivers estimate that they will be able to travel the extra distance required by these movements faster than the time they will be delayed prior to making the intended left turn movement. Often, reduced travel time does not result from the right turn, left turn movement. In fact, it has been found that performing a u-turn results in a longer travel time or delay than waiting to perform a left turn (Liu et al. 2007).

Related to roadway and intersection geometry, is overall transportation infrastructure design. Right lanes often show lower saturation rates or vehicle counts than middle or left lanes on multiple lane roadways because less aggressive drivers use the right lane and because worse pavement conditions are often present (Perez-Cartagena and Tarko 2005). Another roadway design factor that can impact traffic flow is location of bus stops. Busses stopped on roadways cause traffic to deviate from the right lane to continue. This has the potential to cause congestion. The longer a bus waits at a stop and the closer the stop is to the intersection, the more likely congestion is to occur in and around the intersection, potentially impacting the network as a whole (Rahka and Zhang 2004).

Signal timing is another major factor that impacts traffic volume and travel time. Improperly timed signals have the potential to reduce roadway capacity and increase travel time. Well timed signals have the potential to increase roadway traffic counts and reduce travel time. Regarding turns, it should be noted that protected only phasing causes the highest delay to left turning traffic (Asante 1992). On poorly design left turns, this delay can cause vehicles waiting to turn to queue into the mainline vehicular traffic. Situations like this are dangerous and can cause congestion and delays in the mainline traffic. It is obvious that poor signal timing can cause delays at the intersection where the timing is being used, however, poor signal timing can cause delays in traffic upstream. In fact, upstream delay induced by downstream traffic can be caused by improper offset of signal green times (Ahmed et al. 2013).

Attempts have been made to increase the travel speed and reduce the travel time of transit travel options like busses. In order to expedite bus travel, transit options have been given signal priority. This means that they are allowed to maintain their travel speed and route, even if it causes an out of sequence signal cycle. Creating networks that allow for this action can result in some positive and negative effects. A positive effect is that fast moving bus routes may attract more riders, creating a high O-D demand for the stops on the selected route. Specifically, when selecting bus routes, users choose routes that give them the shortest amount of travel time (Goh et al. 2014). This behavior would obviously give bus routes with low travel times higher usage rates than routes with larger travel times. It is somewhat unclear how bus route O-D demands interact with overall network O-D demands. That being said, research has found that giving transit vehicles signal priority can cause delay at the intersection and in the overall network, especially, as the number of transit vehicles increases (Rahka and Zhang 2004). It was unclear at which level of transit prioritization and individual user accommodation should be implemented to minimize travel time and optimize transportation network usage efficiency.

### 2.2 Social Network Analysis

This section provides background information on Social Network Analysis. SNA has been in use for at least 100 years (Jasny 2012). In the mid 1800's, the first mathematical model applied to a social network study was developed, with SNA really coming into use in the 1960's when the first computers were available, then through the 1970's where only one or two network properties could be studied using computers, to the 1980's and today when the microcomputer enabled more complex SNA studies (Freeman 2006). SNA has been used to study a wide variety of topics. SNA has been applied to the study of gang violence in Los Angeles, ancient politics and people organizations, e-learning environments, the social aspects of the recent Egyptian revolution, insects, general communication, child psychology, criminal intelligence and terrorism, industrial organization and post war people displacement. Though frequently associated with social sciences, SNA has evolved into a normal science. Freeman writes that a normal science exists when scientists share a paradigm and work together in a systematic effort to advance their field of study (2006). SNA is a normal science because it uses graphs to study and communicate information, uses mathematical tools for modeling and uses computers to analyze large amounts of data (Freeman 2006). SNA research is similar to typical research but also very distinct in its research focus and the results it produces. Conventional research focuses on comparing attributes of individual components of the study to determine how similar or dissimilar they are, while SNA looks at actors to determine how they are embedded within a network, as well as, adjacent actors to determine holistic patterns of the entire network (Hanneman and Riddle 2005). SNA does this through building a network of actors and their mutual relationships as ties or edges (Trier 2008). Traditional research defines actors by their individual uniqueness and/or similarities to other actors. SNA evaluates individuals and actors in regards to their relationships with other actors. SNA defines actors by their relationships and position within a selected network. The data that SNA collects on the actors and relationships studied can be scaled in binary, multiple category, grouped ordinal, full rank ordinal, and interval measures of relations (Hanneman and Riddle 2005). Data collected can be input in yes/no, type, grouped ranking number, full ranking number, and scaled ranking. The various data types and scales can then be analyzed to study the makeup of a selected social network.

The decision making of committees has been studied such that it can be determined how individuals make decisions. Some individuals may make decisions without as much influence from the overall committee. However, committees often make decisions that are very similar to the decisions or opinions of individual committee members. Researchers studied whether individuals and the committee would reach the same decision given identical data. Specifically, a committee that determines the interest rate for a bank in England was studied. The correct committee decision was determined based on previously developed and verified models. Researchers found that individually and as a committee, decisions varied little from the previous period (Bhattacharjee and Holly 2013). Typical committee member relationships had a high strength and high level of interaction (Bhattacharjee and Holly 2013). These findings indicate that there is strong and frequent communication amongst the committee members and that upon discussion, members generally agree with each other. Because little change in interest rate occurs from month to month it also indicates that the committee has historically made correct decisions which only require minor adjustments during the next period.

Influence of a small sets of nodes can be critical within a social network. This small group of nodes could be considered "power players" within a much larger network. They may have a high level of centrality with the ability to positively or negatively influence a network. Researchers have worked to determine the seed node size required to influence a selected network. Though this type of SNA is relatively new, validated the use of a model that determined that as the seed size increases, the positive or negative influence increases (Li et al. 2014). Though this is somewhat intuitive, previous research has not studied the use or effectiveness of mathematical and technology based models when evaluating node or seed influence. This method is useful because it can evaluate the influence of nodes and seed groups quickly and correctly (Li et al. 2014).

The interaction of various groups during the development of urban regeneration programs in Europe has been studied using SNA. Generally, it was determined that uneven distribution of power and resources impacted the overall planning and program decision making process (Bull and Jones 2006). This indicates that groups in positions of power and with greater resources influenced the process more than other, possibly, more knowledgeable and useful groups. Finances, political connections outside of the groups, competing interests, uncooperative group members, trust, and ineffective laws often created ineffective power balances amongst the groups (Bull and Jones 2006). These causes of power imbalances are somewhat common assumptions which were verified as potential causes of power imbalances in this research.

SNA research has studied which connection configurations are most effective in communicating. One study found that Bi-fan configurations are the most effective (Zhang et al. 2013). Essentially, bi-fan networks are configured in the same manner that a one-way street network is configured. In this setup, communication is directed with nodes either receiving or giving communication to the nodes adjacent to their location. Transferred to transportation planning, this method indicates that intersections are best able to handle traffic flow in two directions only. Research has also found that nodes with strong prior relationships with their neighbors will maintain a strong connection, however, strong third party ties may weaken the direct connection strength of two nodes because if connecting better with a 3$^{rd}$ node looks attractive, multiple related nodes may change their connection focus (Greve et al. 2010). This would indicate that increasing the capacity of an intersection can alter the tie strength and centrality of a network. For example, in a network with major collector streets and intersection along with multiple minor streets and intersections experienced a capacity change at a major intersection area, local traffic volumes and intersection tie strengths would change. The strength of adjacent major intersection ties would change, as well as, the strength of the minor intersection ties connected to the major intersections. Depending on the change in connection strength with the intersections directly adjacent to the modified intersection, the traffic volume (connection strength) of 2$^{nd}$ and 3$^{rd}$ step reach intersection would be either pushed to or pulled from the changed intersection.

SNA of medical relationships and communication structures is a common focus of SNA research. Medical networks and relationships can be quite large in hospitals, making understanding them complex and time consuming. As a result, developing and implementing change can be difficult and time consuming. When implementing change, researchers determined that identifying nurses that are central to operations, with high levels of influence, are critical for success (Pow et al. 2011). Essentially change champions, these central individuals are very helpful in influencing others to learn and adopt changed systems and tools.

SNA model development can be static or dynamic in nature. When time is a critical component of model development, a dynamic model should be implemented. A static network is a snap shot of an SNA model (Zhou et al. 2011). A dynamic model enables researchers to determine how important nodes came into specific positions and if their status is already diminishing (Trier 2008). In the study of traffic congestion, a dynamic model would take into account network congestion and intersection importance at any given point in time. For example, a specific intersection and its edges may be studied to determine how and when it becomes congested. Simply studying the same intersection in a static manner would only consider its state of congestion at a certain point in time. A static SNA study would not consider the traffic conditions before or after the study. If congestion was occurring at the time of the study, the network conditions leading to the congestion event, as well as, the conditions leading to a non-congested state would be unknown. As such, it would be difficult to determine how to mitigate congestion and how to model potential solutions. One study that focuses on social network analysis in coaching evaluated networks and nodes in three functions. It found that SNA can be used in the following manner:

- Identify the current state of the network to determine how the overall network may be changed;
- Determine which individuals may be need to be evaluated, perform evaluations, develop implementation plans, and then carryout the required changes;
- Measure the benefits of modifying or altering individuals, as well as, the overall network (Terblanche 2014).

Though this study focused on a team based social network and improving coaching, the finding could be applied to improving transportation networks through issue identification, plan development, and measurement of impact the changes had on network performance.

Other SNA research has found that distance and cost of a relationship impact the strength of a tie (van den Berg et al. 2012). Simply put, this means that a tie between two nodes that covers a long distance or requires a high cost (effort, time, dollars) to maintain will likely have a weaker strength. Weaker tie strength will result in nodes being assigned lower centrality values. In a transportation network, a rural section of a network would likely carry less traffic than a suburban network, resulting in this part of the overall network being less central or critical to network performance.

SNA applications in traffic congestion are worthy of study because, in general, SNA use has not been fully explored (Rodriguez Diaz 2009). SNA cycles and their associated dynamics and structures can become predictive or explanatory during their study which enables users to make predictions about future events and aid in influencing positive future events (Rodriguez Diaz 2009). This knowledge is very useful to the traffic congestion problem. Developing a predictive model that aids in predicting future congestion in a specific traffic network would be beneficial to network users. Developing a SNA model that enables decisions makers to positively influence future events would be very beneficial to transportation networks, improving the sustainability of a network and society, as a whole. Developing a social network of intersections and roadways could also be integrated with traditional social network studies. This step of linking transportation engineering and planning to the social science of travel patterns has not been done before but would be an innovative tool if done and proven successful.

### 2.2.1 Social Network Analysis Terms and Definitions

In SNA, there are many familiar terms with unique definitions. The terms related to traffic congestion and brief definitions are provided below.

- Nodes – also known as actors are the individuals or organizations that make up social networks (Hanneman and Riddle 2005). In this research, intersections are considered nodes.

- Edges – are the connections or relations between nodes two nodes (Hanneman and Riddle 2005). Roads connecting intersections are considered edges during the research.

- Adjacent – two nodes are adjacent when they share an edge (Friedkin 2011).
- Degree – is the number of nodes adjacent to a selected node (Park et al. 2011).
- Path – a sequence of consecutive edges (Loosemore 1998).
- Closed walk – is a path that can involve the same node or edge multiple times but begins and ends with the same node (Hanneman and Riddle 2005).
- Cycle – is a path of three or unique nodes, except for the node that the path begins and finishes with (Hanneman and Riddle 2005). A cycle is different than a closed walk in that no edges are repeated and the only node that is used more than once is the beginning and ending node.
- Distance – number of edges that make a path (Loosemore 1998).
- Density – is the fraction of possible edges within a network (Friedkin 2011). A high density indicates that the nodes within a network are well connected and that few structural holes are likely to exist.
- Sparseness – is a low density of nodes in SNA and is a result of budget constraints in time or money (Cowan and Jonard 2009). In addition to being applied to nodes, the definition of sparseness can be applied to the edges or potential edges within a selected network.
- Neighborhood – is the subset of adjacent nodes, for a selected node (Park et al. 2011). The clustering coefficient measures the density of the selected neighborhood (Park et al. 2011).
- Geodesic distance – is the length of the shortest path between two nodes (Hanneman and Riddle 2005).
- Direction – is the source of the connection. For example, in a two node network, one node may perform all of the communication and one node receives all communication. The direction of this network would be one way. Related to direction is the understanding that networks can be directed or undirected. In undirected networks, two nodes are connected no matter which one initiates the connection and which receives. A node's indegree is the number of nodes that that supply relationships to that node and a node's outdegree is the number of nodes that accept relationships from that node (Park et al. 2011) A network of directed connections is called a diagraph and defined below.

- Diagraphs – is a plot with directed edges (Loosemore 1998). Directed edges indicate which nodes initiate and which nodes receive edges. In diagraphs, edges can indicate that one or both nodes initiates the edge with the other. In transportation congestion research a diagraph would exist if both two way and one way streets are part of a particular transportation network studied.

- Faction – is a group of nodes which are more tightly connected to each other than members of other factions (Hanneman and Riddle 2005). In transportation networks factions may be different neighborhoods or districts within a city or regional area.

- Structural equivalence – is a measure of how closely a pair of nodes within a network have an identical pattern of contacts (Loosemore 1998). In transportation networks, complete structural equivalence is very rare because many edges are created on a grid layout and most edges do not often overlap.

- Structural fold – situation in which two groups connect and overlap by one node (Vedres and Stark 2010). This situation occurs when two groups share one node which serves as the connection point between the groups. An equivalent definition in traffic congestion terms would be a connection of two neighborhoods, where one shared intersection serves as the connection point between the neighborhoods.

- Structural hole – a gap between two nodes where there is potential for beneficial information flow (Buskens and van de Rijt 2008). A simple example of a structural hole in a transportation network is a gap between two intersections or road end points caused by a physical obstacle. Structural holes should be avoided in traffic networks.

- Cutpoint – is a node that if removed, would cause a network to be divided into un-connected parts (Hanneman and Riddle 2005). A transportation network situation where a cutpoint may exist would be on either side of a river bridge crossing. If either node is removed, the bridge is removed from the network, dividing it into un-connected parts.

- Bridge – is an edge that would cause the network to become un-connected if removed (Hanneman and Riddle 2005).

- Centrality – describes the social power and influence of a node based on how well connected the node is (Park et al. 2011). The measure of a node's centrality is important because it is an indicator of the network influence in may have (Ahuja, Galletta and Carey 2003). Centrality is the focus of this research and related analysis.

- Eigenvector centrality – an extension of basic centrality in which the centrality of a chosen node is proportional to the centralities of all of the nodes it is connected to (De Stefano et al. 2011).

- Betweenness – it is a component of centrality that measures how much a selected node is between other points in the network (Loosemore 1998). It can be visualized as the node that has the shortest overall path to all nodes in the network.

- Inertia – nodes tend to repeat ties with former partners (Cowan and Jonard 2009). In the study of traffic congestion, knowledge of SNA inertia could be used to study why certain paths experience recurring congestion, while other paths do not.

- Skewness – occurs in SNA when new nodes are attached to existing nodes with larger degrees, increasing their already larger degree (Cowan and Jonard 2009). Skewness could be analyzed in transportation networks to determine if potential modifications or additions will balance or potentially overload a portion of the network.

- Asymmetry – related to skewness, asymmetry is a situation in which most nodes have a smaller degree than the average, with a few nodes having many more than the average (Cowan and Jonard 2009).

- Small world network – it is a network with dense local clustering and short network distances (De Stefano et al. 2011). In SNA, small world network has short path lengths, creating a dynamic situation, with quick information flows, behavioral transfers and behavior coordination (Friedkin 2011). A simple example of this in transportation congestion is an extremely congestion intersection where the adjacent intersections quickly experience increased congestion due to diverting network users.

### 2.2.2 Social Network Analysis Applications Relevant to Traffic Congestion

The literature review also determined there located several published study findings that are relevant to this research. They are relevant because they are a blend of SNA and psychology. This blend is helpful in attempting to improve traffic congestion as network performance is measured while individual decisions impact the performance.

Vaisey and Lizardo conducted a SNA in which they determined that network characteristics are likely to stay the same once they are established (2010). Their study also determined that prior network behavior is a good predictor of future network composition (Vaisey and Lizardo 2010). Using these findings one could predict future network behavior based on previous and consistent network behavior. Knowing that the past, current and future network behaviors will be consistent, means it can be assumed that networks behavior is commonly stable with small fluctuations and change. Any change that may occur would be incremental.

Related to the findings of Vaisey and Lizardo, Jones et al determined that network exchanges are not random or uniform, but patterned based on division (1997). Their findings indicate that nodes within a network interact in patterned ways. It also indicates that nodes interact with, and therefore, affect like nodes. For example, in studying traffic networks of arterial streets, major intersections will be most defined by the other major intersections they interact with. Major intersections will also be most affected by other, similar, major intersections. When planning for a new intersection or transportation network modification, this understanding can be used to help determine what new work or modification should take place, as well as, how this change will impact the network and various specific nodes.

Another study with applicable results is one in which negative interactions were found to disproportionately affect the studied variables (Labianca and Brass 2006). This finding can be related to traffic congestion in which reliability is a major factor in commuters choosing travel routes. A negative traffic congestion interaction that may affect travel route selection is time variability which leads to delayed and late destination arrival times. Transportation network users view late arrivals negatively, even if they occur relatively infrequently. To avoid this negative result, they will often select the travel routes with the most consistent travel times, even if it takes a little longer. Routes that are perceived to have a tendency towards unplanned delays, and negative outcomes, will not be selected.

## 2.3 Social Network Analysis Applications in Civil Engineering

The use of SNA in civil engineering has not been in practice for a long period of time. SNA has been used in civil engineering applications for about the last 20 years. Typical SNA uses in civil engineering are similar to SNA uses in other disciplines, focusing on the relationship makeup of individual people and organizations.

Chinowsky et al. used SNA methods in studying project effectiveness. They introduce the Project Network Interdependency Alignment (PNIA) model which evaluates the actual project stakeholder knowledge exchange against the knowledge exchange requirements of each task relationship (Chinowsky et al. 2011). The development of a PNIA model consists of three steps. The first step involves collecting communication and knowledge exchange data, the second involves evaluating the interdependency of each pair of tasks in the project schedule and the third involves analyzing how well the SNA model and PNIA model align (Chinowsky et al. 2011). The PNIA model translated to traffic congestion mitigation efforts would evaluate the actual traffic volume against the required traffic volume for each pair of intersections. The three steps required to do this would be collecting actual and required traffic volumes, evaluating the interdependency of each pair of intersections and analyzing how well the SNA model and PNIA model align when applying them to traffic congestion mitigation functions. The PNIA model was effectively used by Chinowsky et al. to identify potential stakeholder disconnects and to demonstrate that inappropriate or misaligned communication can cause miscommunication and project delays (2011). Applied to traffic congestion mitigation a similar model may be able to identify potential mismatches in planned versus actual traffic volumes and the resulting traffic delays.

Another civil engineering related SNA study focused on the collaborative ventures of corporations. In this study, individuals, or nodes, were defined as different corporations. Focusing on Korean firms, the SNA of the study determined that large companies experience more profit by broadly strengthening their overall network while small and medium sized companies experience more profit by focusing on building relationships with a few strategically selected large companies (Park et al. 2011). The study also verified that company performance is strongly related to company makeup at the corporate level and not related to individual project performance (Park et al. 2011). Key SNA factors analyzed in developing the study findings were density, direct and indirect ties, indegree and outdegree, as well as, degree centrality, betweenness centrality and closeness centrality (Park et al. 2011).

Two studies focused on the social network of individual projects. Wambeke et al. focus on the social network of the different construction trades involved with a project while Chinowsky et al. focus on the social network of different construction management individuals. Through their study, Wambeke et al. identified mechanical, electrical and drywall subcontractors as the key trades on a construction project (2012). Second eigenvector analysis was used to determine key trades, with number of tasks the determining factor. In their study, Chinowsky et al. indentified several team attributes which lead to poor project performance. The attributes identified for combining to cause poor team performance are over centralized decision making, lack of knowledge and information, lack of trust and isolated individuals (Chinowsky et al. 2008).

It has been determined that certain project types facilitate strong social networks (Ruan et al. 2012). Specifically, collaborative project methods typically utilized in alternative project delivery methods improve project collaboration and social network strength. Construction research regarding SNA has evaluated the best way to communicate to improve safety. For example, depending on the demographics of individuals, certain communication methods work more effectively and build stronger relationships (Carlan et al. 2012). Specifically, SNA methods can be used to create high performance teams and effective stakeholder management which are the two most critical factors to project success (Mohan and Paila 2013). Transferred to SNA of transportation networks, this could match with the fact that different intersections can handle different types and volumes of traffic than others, managing selected intersections in conjunction with nearby intersections, and other related variables are critical to overall transportation planning and management.

## 2.4 Network Analysis and SNA Applications in Transportation Planning

SNA is increasingly being used to evaluate the social networks that utilize transportation networks. Research has begun to examine what social networks utilize certain transportation methods and networks and why. Social networks have been studied so that the social welfare of the traveling population, often focusing on disadvantaged people, can be maximized.

Two related studies indirectly apply SNA techniques in developing methods to mitigate traffic congestion. One study determined that increasing link redundancy and reducing link length are possible traffic congestion mitigation solutions (Jenelius 2009). This study did not study the cost associated with these alternatives. As such, the best alternative could not be determined. A second study evaluated the cost of improving a transportation network against the cost to build a loop around a congested city. The findings of this study determined that travel hours would decrease the most and require the least amount of money to implement by improving the existing travel network (Antipova and Wilmot 2012). Based on these findings, an SNA model that evaluates an existing transportation network to determine exact locations for improvements would likely be cost and travel time effective.

Researchers in Italy have compared SNA measures of connectivity with more traditional methods of transportation planning measurements. This research found the following SNA centrality measure correlations:

1. In general transportation accessibility and centrality measures evaluate the same data from different perspectives;
2. Accessibility is strongly correlated with closeness centrality;
3. Place rank of intersections gives results that are similar to running betweenness centrality analysis;
4. Similar to eigenvector centrality, researchers determined that a zone is more accessible and central if it is linked with other important and well connected zones (Rubulotta et al. 2013).

Taylor performed a type of network analysis that is similar to SNA but focused on network vulnerability. Specifically, he attempted to identify vulnerable network points which would cause major network delays if problems occurred in their area (Taylor

2008). High traffic areas were found to be points of focus and points of vulnerability in a similar study (Murray et al. 2008). These high traffic areas could be considered central based on the higher than average traffic they receive. The vulnerable points in both of the studies discussed roughly match the central points in a social network. One researcher studied the use of online social networks in transportation planning. Several advantages and disadvantages were determine. For example, several ethical and legal concerns regarding the collection of information, most specifically, related to discrimination (Salkin 2011). Positive attributes of using online social networks is generally greater overall participation in studies and real time data collection (Salkin 2011).

Related to this finding is that certain people may fill specific or multiple roles within a specific social network (Green 2007). When applied to roadway networks, this finding indicates that some nodes or intersections may fulfill one or more role within the network. For example, some intersections may only take collector street traffic, whereas, others may take collector street traffic in two directions and neighborhood traffic in two other directions.

In evaluating how social networks of individuals may impact travel patterns, researchers studied elderly and handicapped people. Research indicates that elderly people travel mainly for social functions (Jansuwan et al. 2013). In areas with a high elderly person demographic, it would be likely that the transportation social network would likely be similar to the overall social network of the population in the area. It was also determined that the strength of the social network for handicapped people, which aided them with their transportation needs, was a strong indicator of how mobile these people were (Jansuwan et al. 2013). Using social network analysis to study the travel patterns of the handicapped individuals and the people that aided them would possibly result in centrality measures that are similar to the actual social network of these individuals.

In related research, in person social networks were compared to online social networks. Specifically, offline social networks and health were studied for comparison to online social networks. Based on an extensive review of existing research, it has been proposed that online social networks can be a valuable tool in evaluating a person's health factors and could possibly be used to develop intervention and treatment plans (Durst et al. 2013). This proposed finding indicates that online networks appear to mirror or reinforce offline relationships and networks (Durst et al 2013). Applied to transportation planning, this development would indicate that social networks of individual transportation network users would likely mirror their frequent travel paths and patterns. Individual social networks could be drivers of O-D demand calculations and analyses.

The social network of the public individuals and agencies involved in transportation network planning has been studied. Researchers studied two Canadian communities that participated in pilot Municipal Sustainability Planning (MSP) programs. Through their studies, researchers found that MSP programs helped communities plan in a more sustainable manner (Calder and Beckie 2011). This was accomplished through increased communication and engagement methods where MSP leaders tapped into and strengthened existing social networks, while also adding several beneficial weak ties which enabled them to share information about the MSP programs in a more widespread manner. (Calder and Beckie 2011). In the previous research, the main function of social network analysis was to create a more complete and holistic network to facilitate more sound and sustainable decisions. This method could be expanded to social network analysis of the complete network such that all people, agencies, companies, roadway intersections, bus stops, etc. are incorporated into the decision making process such that the most complete and sustainable decisions are made every time.

In transportation planning, network analysis is a commonly performed function. One particular study focused on the different scale and location of subway and railway transportation networks. Thought somewhat intuitive, the authors determined that railway stations are located at much greater intervals and over a much larger area than subway stations (Louf et al. 2014). The authors worked to determine if there is a correlation between Gross Domestic Product (GDP) and/or Gross Metropolitan Product (GMP) and the number of and distance between railway and subway stations. They found that as GMP and GDP increased, the length and number of stations generally increased for both railway and subway systems (Louf et al. 2014). These results mean that more densely populated and/or more wealthy areas are likely to have more developed railway and subway networks.

Similarly to traditional social network analysis, it was determined that most related research in civil engineering and construction focused on the literal social interactions of individuals. As such, social network analysis has been applied to interactions between individual people and individual companies (in actor roles) in civil engineering and construction. However, no attempts were made in which the network's main actors were not people or organizations controlled by people. Thus, applying this tool to transportation congestion where the actors are intersections is a new and innovative research focus worthy of more in depth study. Results derived from each of these studies could be effectively used to study more projects to improve performance. The models applications. Just as key attributes, functions and individuals were determined for these studies, similar determinations developed could potentially be used in traffic congestion mitigation could be made for SNA use in traffic congestion mitigation

CHAPTER III

METHODOLOGY

## 3.1 Case Study Selection

A total of five case studies were utilized for this research. These studies are located in the Southern United States. Specifically, these studies are located in Louisiana and Mississippi. Four are located within established within individual city limits while one study encompass three cities that are separated by brief rural sections. Studies from the following locations were utilized:

- Case Study 1
  - Location – Baton Rouge, LA
  - Agency with Jurisdiction – Louisiana Department of Transportation and Development
  - Description – Continuous Flow Intersection located at Siegen Lane and Airline Highway. This intersection is located in suburban Baton Rouge.
- Case Study 2
  - Location – New Orleans, LA
  - Agency with Jurisdiction – Regional Planning Commission for Jefferson, Orleans, Plaquemines, St. Bernard, St. Tammany, and Tangipahoa Parishes.
  - Description – Study of Tulane Avenue corridor from Carrolton Avenue to Interstate Highway 10. This study focused on urban street networks in New Orleans, LA.
- Case Study 3

    - Location – Shreveport, LA
    - Agency with Jurisdiction – Shreveport, LA Traffic Engineering Department
    - Description – Intersections utilized were located in urban Shreveport. Ranking of the Traffic Engineering Department's Top 50 Intersections by volume was compared to centrality calculations.
- Case Study 4
    - Location – Jackson, MS
    - Agency with Jurisdiction – Mississippi Department of Transportation
    - Description – Study utilized intersections in urban Jackson, focusing on the area inside I-20, I-220, and I-55.
- Case Study 5
    - Location – Gulfport, Biloxi, and Pascagoula, MS
    - Agency with Jurisdiction – Mississippi Department of Transportation
    - Description – Intersections located in and around the Mississippi Gulf Coast cities of Gulfport, Biloxi, and Pascagoula, MS were utilized for this study.

Figure 3.1 details the location of the five case studies utilized in the research.


Figure 3.1 Overall Case Study Location Map

The study locations were selected because existing traffic count data was easily accessible and they are well traveled areas. The locations represent a diverse set of transportation networks. Three locations are within metropolitan areas whose total population is less than 1,000,000 people. One location has a metropolitan population over 1,000,000 people. A final location encompasses three cities with individual populations of less than 100,000 and an overall population of less than 500,000 people in the metropolitan area. This location is unique in that it serves a large tourist population for much of the year.

## 3.2 SNA Use and Implementation

### 3.2.1 Traffic Volume and Connection Strength

The associated traffic volumes between connected nodes were used to describe the strength of the connection. The higher the traffic count is between two nodes, the stronger is the connection. To evaluate the social makeup of the intersection network, traffic volume data was entered into a social network analysis program. The connection strength of two intersections was considered equal to the traffic volume between the same two intersections. For example, if there is a traffic count of 15,000 between intersection A and B, the connection strength would be 15,000 for the purposes of this research. Traffic counts can vary in different directions which could give different connection strengths into or out of an intersection. That being said, the data that was available for this research was not directed traffic counts. Only the combined traffic count for each direction of traffic was utilized for this research as connection strengths.

Centrality was calculated using multiple functions within the Unicet 6 social network analysis software. Essentially, each type of centrality quantitatively measures the power or importance of a chosen node. Relative to transportation planning, a central intersection should be one that is given more focus to maintain consistent and non-extended travel time. Performance of central intersections drives the overall performance of the area roadway network. For instance, if an intersection that is central to the network is improved, the overall travel time will improve. However, if a non-central intersection is improved, the network will likely see little improvement in reducing travel time and travel time variability. To determine which intersections are most important for this research, four types of centrality were analyzed. They are defined below:

- Bonacich Power – a degree centrality measure that determines node centrality based on the degree centrality and power of adjacent nodes (Borgatti et al. 2002). Having connections with high numbers of connections results in a high centrality value. High levels of power is associated with being connected to nodes with few other connections (Borgatti et al. 2002). A node could have a high Bonacich power by being connected to both nodes with high or low numbers of additional connections. For this study, power could be achieved by an intersection that is connected to an intersection with low volumes of traffic. Higher centrality values could be achieved by an intersection that is connected to other intersections with high volumes of traffic.

- 2 Step Reach – determines centrality by summing the number of other nodes within 2 steps/links of a particular node (Borgatti et al. 2002). This is calculation is performed by simply counting the number of additional nodes that may be reached by traveling two links from the focus node. Nodes on the perimeter of a network will struggle to reach high values while nodes that are more central to the network will more easily derive higher 2 step reach values. For this study, 2 step reach is calculated by selecting an intersection and then counting how many other intersections are within two links from the selected intersection.

- Eigenvector – a closeness centrality measure that determines node centrality based on the closeness centrality of adjacent nodes (Borgatti et al. 2002). Closeness centrality is calculated by determining how many connections are required to connect a selected node to all other nodes. Based on how many connections are required, a weighted value is assigned to each node. In this study, closeness centrality is a function of how many intersections lie between any two selected intersections.

- Betweeness – a value to determine how central/between other nodes within the studied network a particular node is. Nodes with a value of zero are on the edge or periphery of the network (Borgatti et al. 2002). In a transportation network, assuming similar traffic volumes, intersections located on a loop roadway would have a lower betweeness measures than intersections located on a roadway that goes through the center of the city and connects many other roadways in the process.

Centrality analysis for each of the aforementioned attributes was calculated individually and compiled in a spreadsheet comparison chart. Analysis was also performed using images. Diagrams for Eigenvector and Betweeness Centrality with node size scaled based on these measures, were analyzed to gain a better understanding of where the “central” nodes were located.  Strength of nodes and clusters can be easily determined using network images. Details for each step of the research are described below.  Specifics on the centrality measures are provided in the results and analysis section of this work, as well as, the Appendices.

The steps required to perform social network analysis as part of this research are detailed below.

1. Gather Traffic Count and/or Case Study Data

    a. Traffic counts from existing data sources were located and utilized for this research.

    b. Where possible, traffic count data that was associated with a previous case study was utilized.  This enabled a more complete analysis and comparison to current transportation planning analyses.

2. Label Key Intersections in the Traffic Count or Study Area

    a. Utilizing Google Earth, key intersections were labeled such that they could be tracked and input into Unicet (Social Network Analysis software).

    b. Key intersections in this research were those that are located on major surface streets.  In rare occasions, residential or rural roadways that intersected with major intersections were considered key and utilized for this research.  Where there was a great distance between major intersections or these minor roadways carried exceptionally large traffic volumes, there were labeled and included in the Social Network Analysis study.  This was done so as to not create any gaps or holes in the network.

3. Label Roadway Links with Traffic Counts

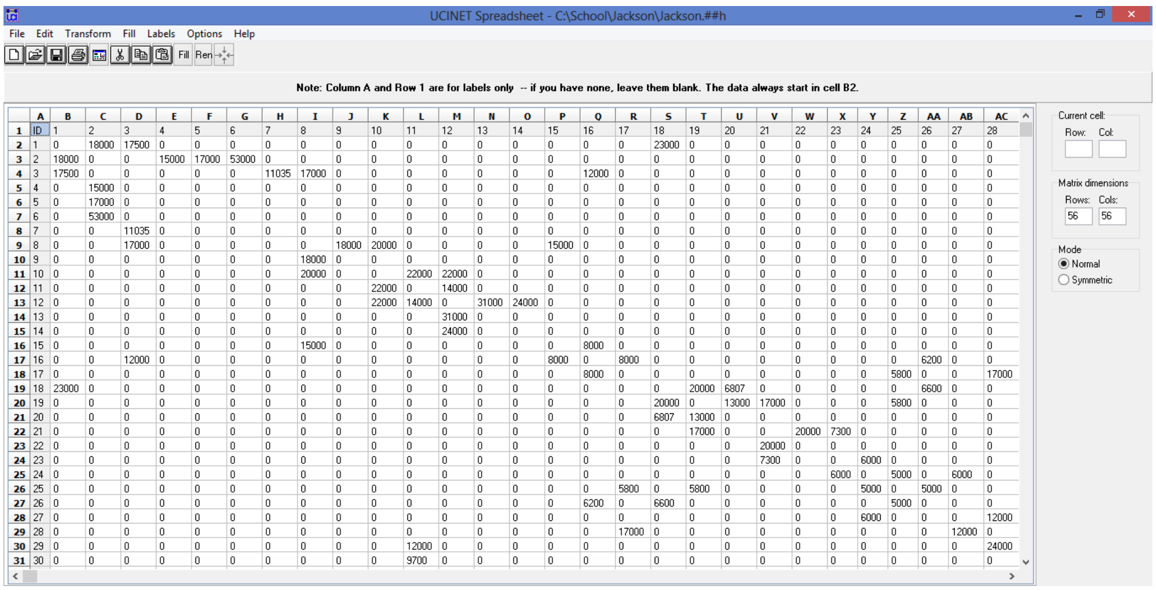
    a. Traffic count data was utilized to label the roadways between the already labeled intersections.

    b. Traffic count numbers were the strength of connection between two adjacent intersections.  The higher the traffic count, the greater the strength of connection between two intersections.

4. Input Traffic Count Information into Unicet Spreadsheet

a. In this step, a matrix spreadsheet was created in Unicet where every intersection node was input on both the X and Y axis. Traffic counts were then input into the two cells that corresponded intersection connections. These spreadsheets can be reviewed in the Appendices of this work.

b. For example, if intersection A was connected to intersection B with a traffic count of 1,000, the strength of connection input into cell A-B and B-A was 1,000. This theory was repeated for each connection in each case study until complete networks were setup in Unicet. See Figure 3.2.




| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | Y | Z | AA | AB | AC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | ID | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
| 2 | 1 | 0 | 18000 | 17500 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 2 | 18000 | 0 | 0 | 15000 | 17000 | 53000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 3 | 17500 | 0 | 0 | 0 | 0 | 0 | 11035 | 17000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 4 | 0 | 15000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 5 | 0 | 17000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 6 | 0 | 53000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 7 | 0 | 0 | 11035 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 8 | 0 | 0 | 17000 | 0 | 0 | 0 | 0 | 0 | 18000 | 20000 | 0 | 0 | 0 | 0 | 15000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20000 | 0 | 0 | 22000 | 22000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22000 | 0 | 14000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22000 | 14000 | 0 | 31000 | 24000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 31000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 16 | 0 | 0 | 12000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8000 | 0 | 8000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6200 | 0 | 0 |
| 18 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5800 | 0 | 0 | 17000 |
| 19 | 18 | 23000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20000 | 6807 | 0 | 0 | 0 | 0 | 0 | 6600 | 0 | 0 |
| 20 | 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20000 | 0 | 13000 | 17000 | 0 | 0 | 0 | 5800 | 0 | 0 | 0 |
| 21 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6807 | 13000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17000 | 0 | 0 | 20000 | 7300 | 0 | 0 | 0 | 0 | 0 |
| 23 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7300 | 0 | 0 | 6000 | 0 | 0 | 0 | 0 |
| 25 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6000 | 0 | 5000 | 0 | 6000 | 0 |
| 26 | 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5800 | 0 | 5800 | 0 | 0 | 0 | 0 | 5000 | 0 | 5000 | 0 | 0 |
| 27 | 26 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6200 | 0 | 6600 | 0 | 0 | 0 | 0 | 0 | 0 | 5000 | 0 | 0 | 0 |
| 28 | 27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6000 | 0 | 0 | 0 | 12000 |
| 29 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12000 | 0 |
| 30 | 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24000 |
| 31 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9700 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Figure 3.2 Unicet Data Input Screen Shot

5. Run Unicet Analysis for the Four Centrality Factors

a. During this step, Unicet was utilized to run Bonacich Power, 2 Step Reach, Eigenvector, and Betweeness Centrality measures.

b. Each report was saved for later use.

c. Raw numerical data was exported to Excel so that rankings could quickly and accurately be made.

6. Run NetDraw to Develop Network Diagrams

a. NetDraw, which is graphical function within the Unicet software, was run for Eigenvector and Betweeness Centrality for each case study.

b. The diagrams generated were saved for later use.

7. Use Diagrams to Visually Verify that Holes or Extra Links are Included

a. Holes (missing connections/links) and extra connections/links, if any, were identified.

b. If any were identified, revisions to the base data set were carried out to ensure a complete and 100% accurate model was created.

c. This step was repeated until a complete and accurate base data set was created.

8. Organize "Top Ten" Ranking Intersections in Each Centrality Measure in Tables

a. For each centrality measure, the "Top 10" ranking intersections were identified.

b. These intersections were ranked in descending order. For each case study, the "Top 10" intersections for each centrality measure were ranked and then compiled in a summary table.

9. Analyze Tables and Diagrams to Determine Which Intersections are the Most Central to the Case Study Area

a. Trends amongst the ranked intersections were identified. The Social Network Analysis Flow Chart below summarizes the steps taken to gather traffic data and analyze it using centrality measures derived through social network analysis.

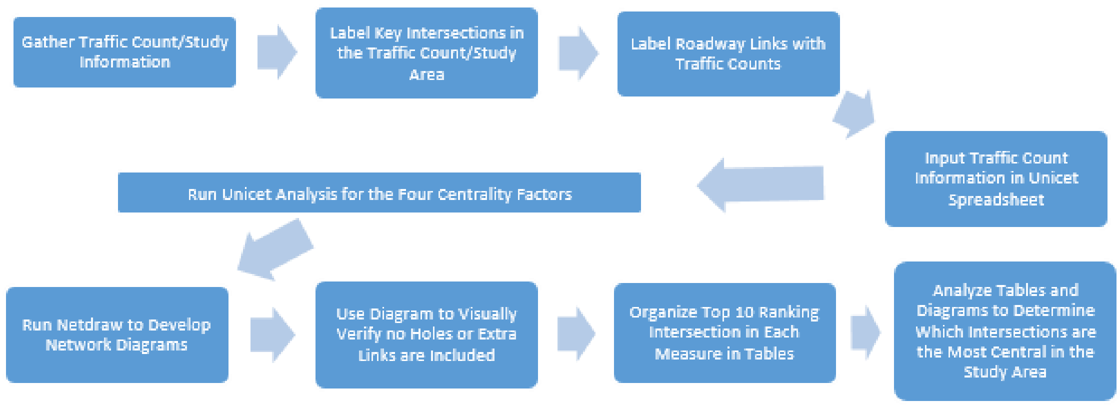



Figure 3.3 Social Network Analysis Flow Chart

### 3.2.2 Case Study 1

The first case study was based on a continuous flow intersection (CFI) in Baton Rouge, LA. CFI's maintain "continuous" flow by allowing left turn and through traffic movements of perpendicular streets to occur at the same time. CFI's allow left turn traffic to cross over on-coming traffic while perpendicular traffic of a cross street is allowed to proceed through. Once left turn traffic has been given time to cross over to the left side of opposing traffic lanes, the signals are changed, allowing opposing traffic to proceed while also allowing left turns to take place unimpeded. This is because left turn traffic has already moved to the left of on-coming traffic. The data for this study is focused around the intersection of US 61 (Airline Highway) and LA 3246 (Siegen Lane). Data was obtained from a study that evaluated the change from a typical four leg signalized intersection where each approach consisted of two through lanes, two left turn lanes and a dedicated right turn lane to a continuous flow intersection (CFI) (LADOTD 2007). Figure 3.4 details the location, intersections included and numbering system utilized in analyzing the first case study. This specific location was selected because of the abundance of traffic count data for intersections located within the "neighborhood" of this intersection.

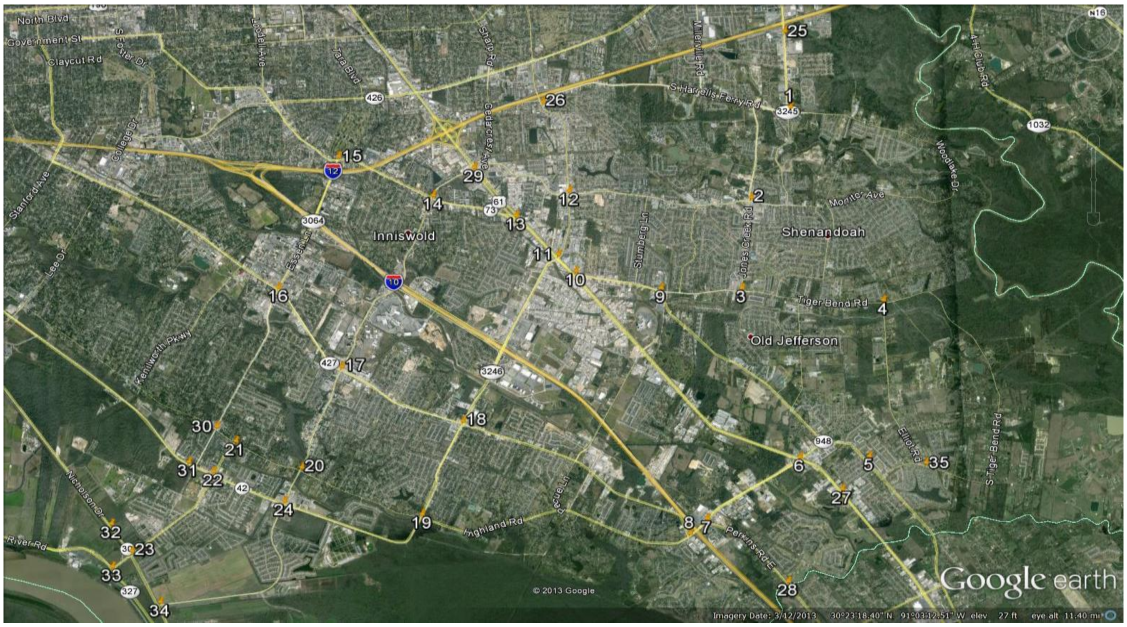



Figure 3.4 Baton Rouge Transportation Network Map – CFI Study

Based on traffic congestion information provided in the LADOTD report, the model development process involved identifying 35 nodes or intersections, which would have traffic volumes studied.

### 3.2.3 Case Study 2

The second case study involved the Tulane Avenue Feasibility project in New Orleans, LA (Regional Planning Commission 2011). This project represents a pre-construction/change study, and though does not have before and after information, it involved abundant data about the local network for the intersection as well as associated businesses and stakeholders. The related network map was plotted in a manner similar to case study 1. Similar analysis to the one described for the first case study was also conducted for the second case study. Figure 3.5 diagrams the area and layout of the intersections utilized.

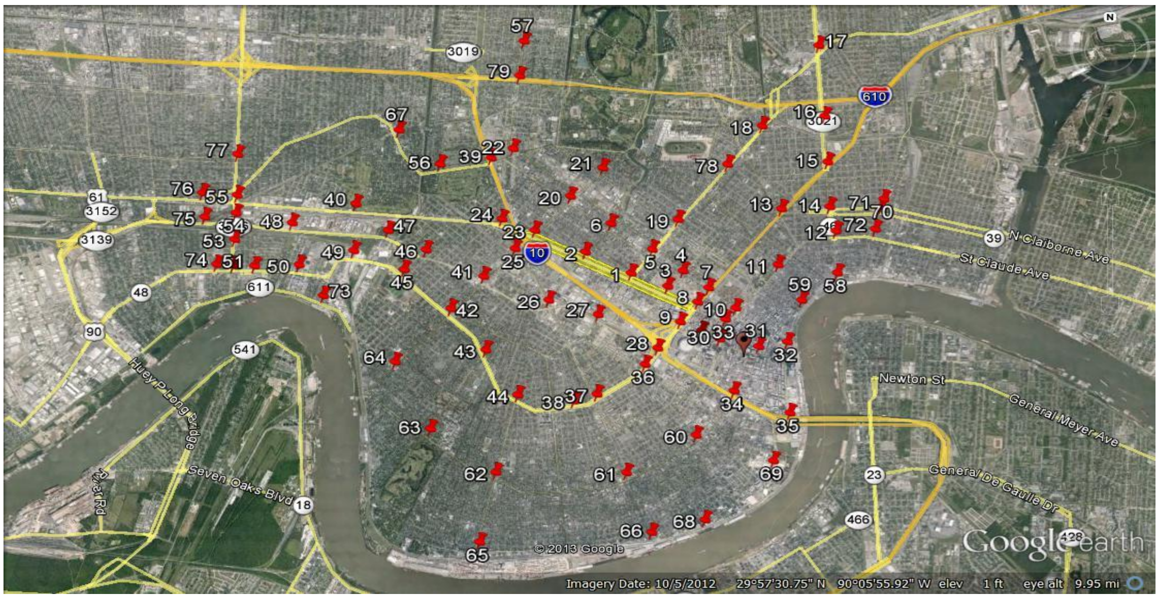



Figure 3.5 New Orleans Network Map & Layout

### 3.2.4 Case Study 3

The third case study analyzed traffic data in Shreveport, LA. The traffic engineering department of Shreveport, LA posts annual traffic counts in a report. This report also lists the intersections with the highest traffic volume. For the purposes of this research, the traffic counts for various roadways was used. Intersections which were ranked in the Shreveport traffic report were labeled with their rank. Intersections not ranked in the annual traffic counts report but used in this case study were labeled with letters to differentiate between city ranked intersections and other intersections used for research purposes.  Figure 3.6 details the layout of the intersections and the area utilized for this study.

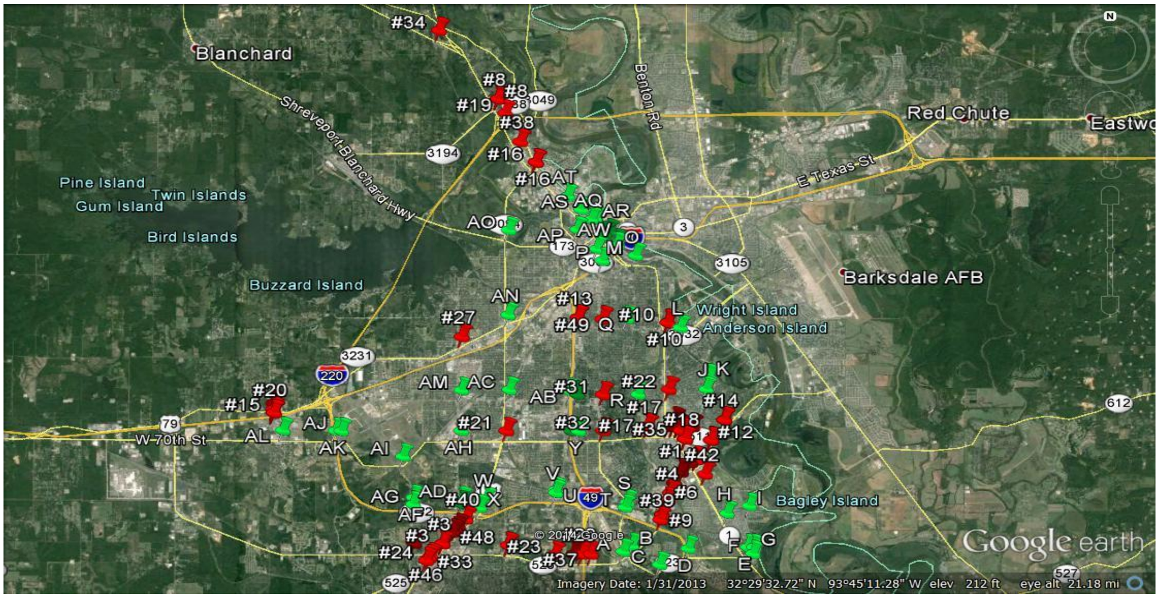



Figure 3.6      Shreveport Network Map & Layout

### 3.2.5 Case Study 4

The fourth case study focused on “principal arterial” streets in Jackson, MS.  This classification and the associated traffic counts are provided on the Central Mississippi Planning and Development District website.  The principal arterial streets used in the research were located in the I-220, I-55, and I-20 triangle within the City of Jackson. This was done to minimize the potential for distortion or shadow that an interstate roadway can cause when analyzing the centrality of roadway networks.  A total of 56 nodes were included in this study.  Figure 3.7 provides a map of the area within I-220, I-55, and I-20 that was utilized for this study.

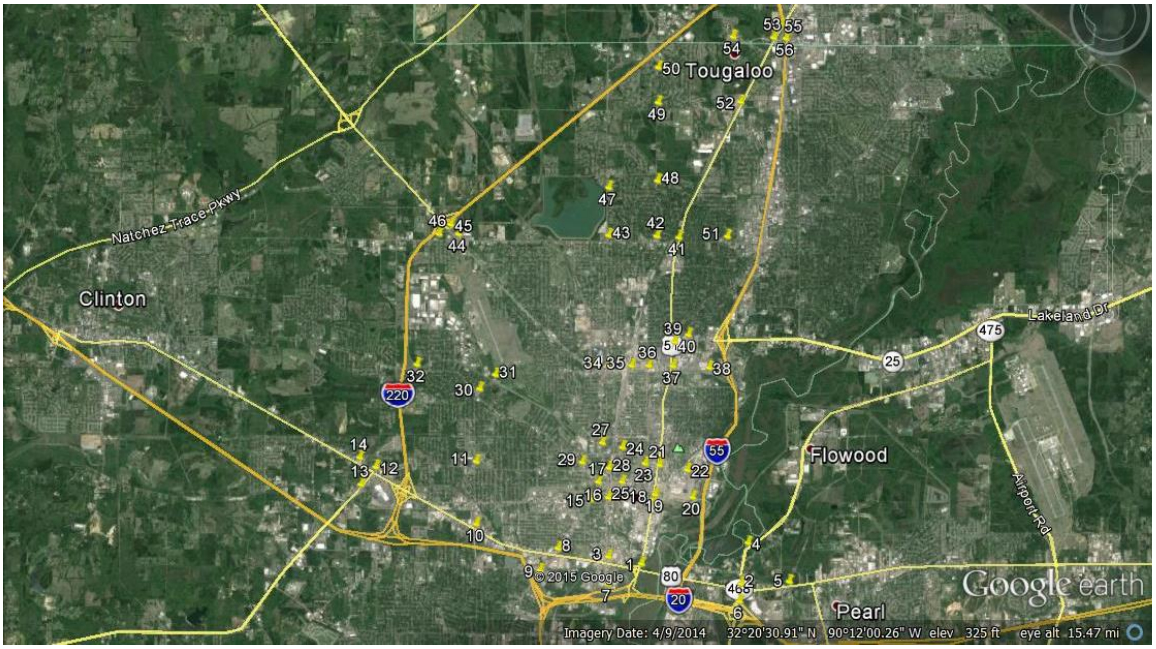



Figure 3.7 Jackson Network Map & Layout

### 3.2.6 Case Study 5

The fifth case study analyzed traffic data in the Biloxi, Gulfport, and Pascagoula metropolitan area. Of the case studies performed, this area included the most rural roadways. It was also adjacent to a popular beach and port area with the full network extending inland to rural areas. A total of 118 nodes located in these three cities and inland rural areas were included in this case study. Figure 3.8 details the Gulfport, Biloxi, and Pascagoula areas that were utilized for this study.

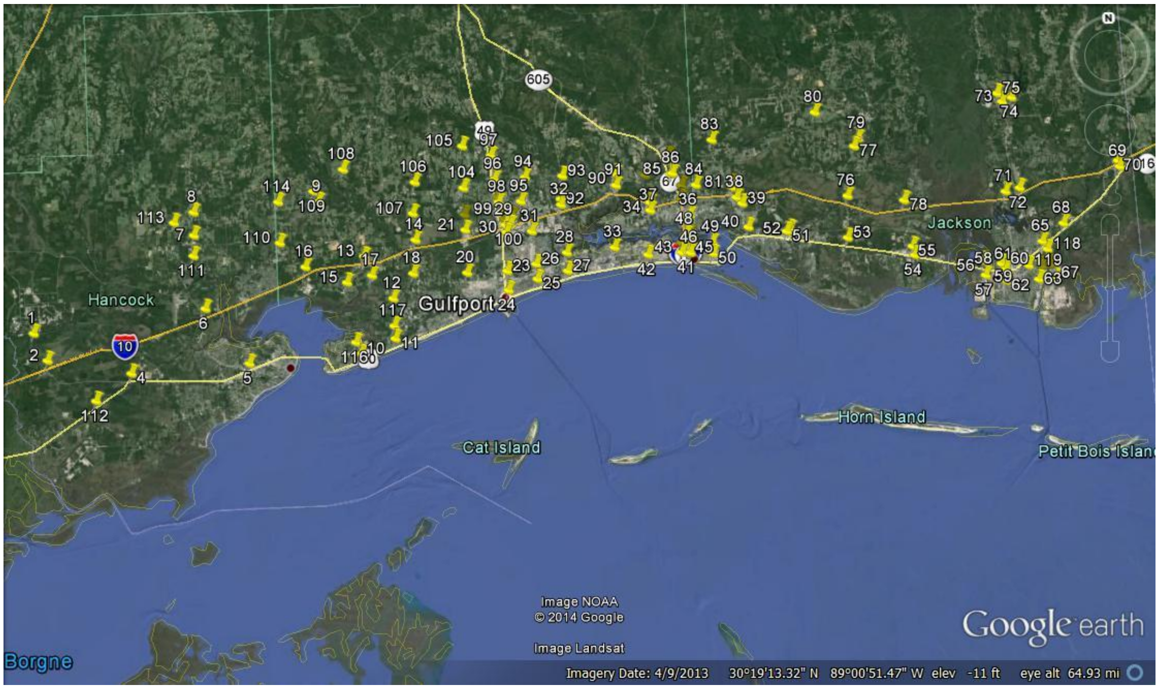



Figure 3.8 Mississippi Gulf Coast Network Map & Layout

CHAPTER IV

RESULTS AND ANALYSIS

## 4.1 Case Study 1 – Baton Rouge Data Output

The centrality measures derived from the data generated for the CFI in Baton Rouge are detailed in the Unicet output below (Table 4.1). In each centrality measure, a larger number indicates that it has a higher centrality measure and is more central to the overall network studied.

Table 4.1 Centrality Measures for All Nodes in Baton Rouge CFI Study

MULTIPLE CENTRALITY MEASURES

--------------------------------------------------------------------------------

| | |
|---|---|
| Input dataset: | Baton Rouge Base File (C:\School\Unicet\Baton Rouge Base File) |
| Output dataset: | Baton Rouge Measures for Dissertation (C:\Program Files (x86)\Analytic Technologies\Baton Rouge Measures for Dissertation) |
| Treat data as: | Undirected |
| Type of scores to output: | Raw scores |
| Value of Beta was: | 0.293685016030104 |
| Principal eigenvalue was: | 3.38798352081216 |

Centrality Measures

| | 1 BonPwr | 2 2Step | 3 Eigenvec | 4 Between |
|---|---|---|---|---|
| | -------- | -------- | -------- | -------- |
| 1 | 136.235 | 5.000 | 0.041 | 35.333 |
| 2 | 224.911 | 9.000 | 0.069 | 69.767 |
| 3 | 123.146 | 7.000 | 0.037 | 43.467 |
| 4 | 50.346 | 5.000 | 0.014 | 13.000 |
| 5 | 84.063 | 6.000 | 0.025 | 31.000 |
| 6 | 237.952 | 9.000 | 0.073 | 101.867 |
| 7 | 315.894 | 8.000 | 0.100 | 91.000 |

Table 4.1 (continued)

| | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|
| 8 | 733.681 | 9.000 | 0.235 | 91.133 |
| 9 | 133.840 | 6.000 | 0.041 | 24.100 |
| 10 | 325.770 | 10.000 | 0.102 | 88.500 |
| 11 | 727.242 | 13.000 | 0.230 | 180.767 |
| 12 | 496.230 | 10.000 | 0.156 | 128.450 |
| 13 | 588.590 | 8.000 | 0.187 | 17.550 |
| 14 | 730.549 | 9.000 | 0.233 | 59.100 |
| 15 | 361.482 | 6.000 | 0.115 | 7.333 |
| 16 | 493.491 | 7.000 | 0.158 | 30.667 |
| 17 | 987.690 | 13.000 | 0.316 | 87.400 |
| 18 | 1052.056 | 12.000 | 0.337 | 159.017 |
| 19 | 1120.027 | 10.000 | 0.360 | 154.833 |
| 20 | 1073.376 | 11.000 | 0.345 | 59.883 |
| 21 | 592.548 | 9.000 | 0.190 | 31.100 |
| 22 | 613.088 | 10.000 | 0.196 | 87.133 |
| 23 | 359.379 | 7.000 | 0.114 | 66.667 |
| 24 | 940.968 | 10.000 | 0.302 | 139.067 |
| 25 | 41.010 | 3.000 | 0.012 | 0.000 |
| 26 | 187.745 | 6.000 | 0.058 | 24.600 |
| 27 | 70.883 | 4.000 | 0.022 | 0.000 |
| 28 | 93.773 | 3.000 | 0.029 | 0.000 |
| 29 | 536.147 | 8.000 | 0.170 | 34.067 |
| 30 | 320.954 | 6.000 | 0.103 | 12.000 |
| 31 | 181.055 | 4.000 | 0.058 | 0.000 |
| 32 | 106.544 | 4.000 | 0.034 | 0.000 |
| 33 | 106.544 | 4.000 | 0.034 | 0.000 |
| 34 | 383.892 | 7.000 | 0.123 | 35.200 |
| 35 | 41.474 | 4.000 | 0.012 | 13.000 |

---------------------------------------
Running time: 00:00:01
Output generated: 07 Feb 15 14:27:17
UCINET 6.501 Copyright (c) 1992-2012 Analytic Technologies

### 4.1.1 Case Study 1 – General Discussion

As noted in the Chapter 3, the data above was exported to Excel which enabled a quick and accurate ranking for each node in each centrality measure. Though each node can be ranked from top to bottom for each centrality measure studied, the highest ranking nodes are most critical for this research. As such, a "Top Ten" list of intersections for each measure was generated. This ranking is detailed in Table 4.2. For this study, node 11 and node 19 each ranked number one in two of the centrality measures. As shown in Figure 3.3, Node 11 was the CFI intersection of US 61 (Airline Highway) and LA 3246 (Siegen Lane). Interestingly, the traffic volume at the intersection represented by node 11 increased after construction of the CFI, as reported in the case study. This result indicates that this intersection is central to the network studied, aligning with the general findings of the social network analyses. As such, this intersection is critical to the overall level of traffic congestion within its network. For instance, in a more restricted state, prior to constructing the CFI, the intersection was more congested with higher delay times and reduced traffic volume. As a result, the other intersections within the network had to carry higher traffic volumes and likely higher congestion. Upon construction completion, the CFI carried a higher traffic volume with reduced congestion delay times. The congestion of this intersection was reduced while also improving the traffic volume it can handle. This change likely reduced the traffic volume at other intersections within the network, reducing the overall congestion delays within the network. This ability makes node 11 central and very important to the congestion of the overall network.

Node 19 was ranked first in two centrality measures and highest overall. In addressing the high overall centrality measure rankings of node 19, these indicate that it is an important intersection within the overall network. This social network analysis tool can be used to identify intersections which may require additional study and potential redesign or reconstruction to improve the network as a whole.

Interestingly, the Bonacich Power and Eigenvector Centrality rankings are identical for the Top Ten ranked nodes. As Bonacich Power incorporates power into its calculation, this finding is a good indicator that the "Top Ten" intersections are both central and powerful meaning they are critical pieces of the overall network, whereby any changes to them would impact the greater network. These factors match but rank the intersections differently than 2 Step Reach and Betweeness because node 19 and other nodes are located on the edge or towards the periphery of the network. Generally, low 2 Step Reach and Betweeness values will be realized by intersections located on the outskirts of the network.

Table 4.2 Centrality Measures Summary and Rankings by Node for First Case Study

| | **Bonacich Power** | | **2 Step Reach** | | **Eigenvector** | | **Betweeness** | |
|---|---|---|---|---|---|---|---|---|
| **Rank** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** |
| **1** | 1,120.03 | 19 | 13.00 | 11 | 0.36 | 19 | 180.77 | 11 |
| **2** | 1,073.38 | 20 | 13.00 | 17 | 0.34 | 20 | 159.02 | 18 |
| **3** | 1,052.06 | 18 | 12.00 | 18 | 0.34 | 18 | 154.83 | 19 |
| **4** | 987.69 | 17 | 11.00 | 20 | 0.32 | 17 | 139.07 | 24 |
| **5** | 940.97 | 24 | 10.00 | 10 | 0.30 | 24 | 128.45 | 12 |
| **6** | 733.68 | 8 | 10.00 | 12 | 0.23 | 8 | 101.87 | 6 |
| **7** | 730.55 | 14 | 10.00 | 19 | 0.23 | 14 | 91.13 | 8 |
| **8** | 727.24 | 11 | 10.00 | 22 | 0.23 | 11 | 91.00 | 7 |
| **9** | 613.09 | 22 | 10.00 | 24 | 0.20 | 22 | 88.50 | 10 |
| **10** | 592.55 | 21 | 9.00 | 2 | 0.19 | 21 | 87.40 | 17 |

### 4.1.2 Case Study 1 – Betweeness Centrality

The Betweeness centrality is shown in Table 4.2 where the "Top Ten" most central (i.e. important and powerful) nodes as determined by four different measures are detailed. It is interesting to note that node 19 was highly ranked in two different measures - that based part of the centrality calculation on the centrality of each node connections - even though it was towards the edge of the network. In addition, node 11 is shown as the largest node in the network in the Betweeness diagram. It clearly shows that node 11 has the highest Betweeness centrality in the network. Reviewing the network Betweeness centrality diagram also shows that node 11 is not in the center of the network. There are roughly 15 nodes to the right of node 11 and 19 nodes to the left of node 11, indicating that the network may not be totally balanced on either side of it. However, using Betweeness centrality indicates that this node is "between" all other nodes and the node with the highest centrality in the network. Figure 4.1 depicts the layout and Betweeness centrality this case study.

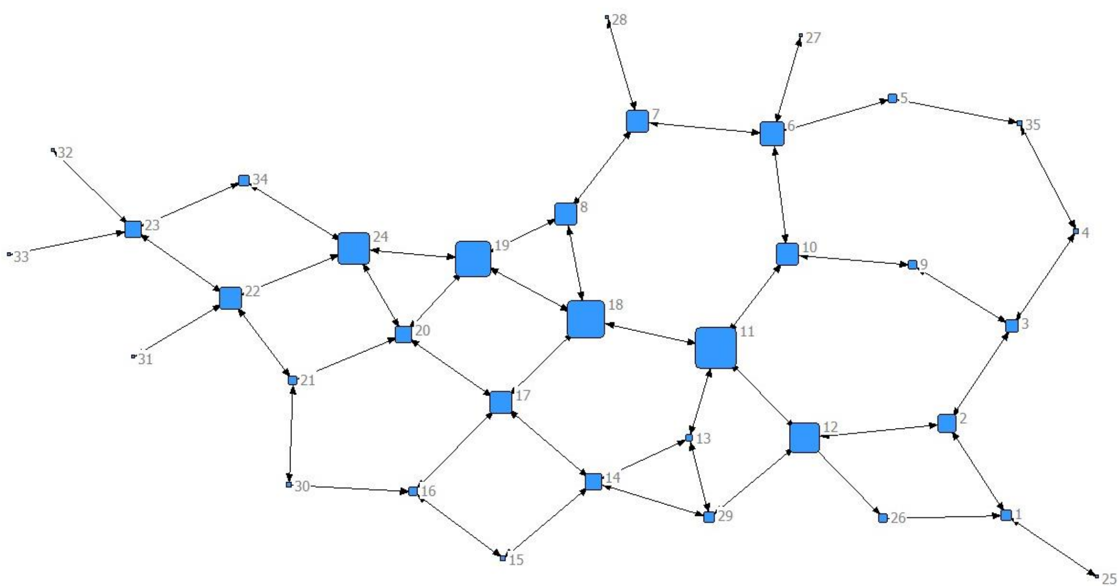



Figure 4.1 Network Betweeness Centrality Diagram for First Case Study

### 4.1.3 Case Study 1 – Eigenvector Centrality

When computing the Eigenvector centrality of the case study 1 network, it was determined that node 19 had the highest Eigenvector centrality value and was most central to the network. When trying to understand why this result occurred, it was determined that the connections had much higher values than connections located on the other side of the network. This was especially true of edges located on the perimeter of the network. Typically, perimeter connections often have lower values which is true for many of the perimeter connections located towards the east perimeter of this network. However, many of the connections located on or near the west perimeter of this network maintained high values. Thus, node 19 was assigned the highest Eigenvector centrality measure. See Figure 4.2 for details.

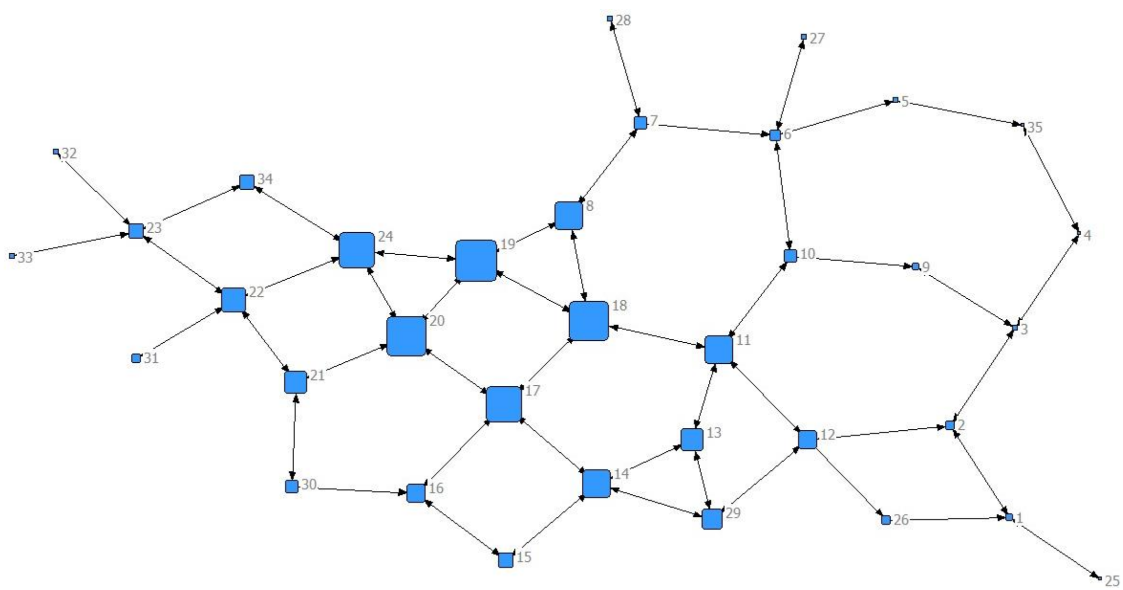



Figure 4.2 Eigenvector Centrality Diagram for First Case Study

### 4.1.4 Case Study 1 – Bonacich Power

When computing Bonachich Power centrality, which is an indicator of how well a node's connections are connected, matches Eigenvector centrality for the "Top Ten" ranking nodes (Table 4.2). Each of the "Top Ten" nodes was ranked in the same position for these centrality measures.  Given that Bonacich Power and Eigenvector centrality consider the centrality of nearby nodes when determining overall centrality measures, this is a strong indication that the "Top Ten" nodes, as ranked by these measures are central to this network

#### 4.1.5 Case Study 1 – 2 Step Reach

The 2 Step Reach centrality measure ranked node 11 as the most central in the network.  This centrality measure counts how many nodes are within two connections of the selected node.  It is similar to Betweeness centrality in that nodes on the perimeter of the network will have lower centrality measures.  As such, it had a similar overall node ranking with the "Top Ten" including seven of the same nodes.

### 4.2 Case Study 2 – New Orleans Data Output

The centrality measures derived from the data generated for the Tulane Avenue Feasibility Study in New Orleans are detailed in the Unicet output below (Table 4.3).

Table 4.3 Centrality Measures for All Nodes in New Orleans Tulane Avenue Feasibility Study

MULTIPLE CENTRALITY MEASURES

--------------------------------------------------------------------------------

Input dataset: New Orleans Data Set (C:\School\Dissertation\Unicet Data and Models\New Orleans Data Set)
Output dataset: New Orleans Data Output (C:\School\Dissertation\Unicet Data and Models\New Orleans Data Output)
Treat data as: Undirected
Type of scores to output: Raw scores
Value of Beta was: 0.2815029323096
Principal eigenvalue was: 3.53459902106683
Centrality Measures

| | 1<br>BonPwr | 2<br>2Step | 3<br>Eigenvec | 4<br>Between |
|---|---|---|---|---|
| | -------- | -------- | -------- | -------- |
| 1 | 1102.112 | 12.000 | 0.254 | 381.965 |
| 2 | 1147.531 | 12.000 | 0.265 | 424.121 |
| 3 | 947.090 | 11.000 | 0.217 | 189.636 |
| 4 | 740.506 | 10.000 | 0.170 | 166.615 |
| 5 | 999.950 | 11.000 | 0.231 | 293.816 |
| 6 | 916.050 | 10.000 | 0.212 | 154.278 |
| 7 | 672.847 | 13.000 | 0.153 | 496.771 |
| 8 | 757.437 | 11.000 | 0.173 | 248.568 |
| 9 | 750.140 | 12.000 | 0.171 | 182.354 |
| 10 | 283.209 | 10.000 | 0.063 | 277.335 |
| 11 | 124.175 | 7.000 | 0.027 | 65.372 |
| 12 | 150.799 | 10.000 | 0.032 | 174.728 |
| 13 | 594.835 | 14.000 | 0.135 | 581.876 |
| 14 | 287.898 | 12.000 | 0.063 | 403.536 |
| 15 | 95.234 | 7.000 | 0.020 | 67.612 |
| 16 | 43.304 | 4.000 | 0.009 | 10.000 |
| 17 | 51.491 | 4.000 | 0.011 | 19.388 |
| 18 | 132.508 | 5.000 | 0.030 | 86.388 |
| 19 | 779.306 | 11.000 | 0.180 | 206.439 |
| 20 | 1096.004 | 12.000 | 0.254 | 435.986 |
| 21 | 1031.773 | 10.000 | 0.239 | 167.248 |
| 22 | 997.183 | 11.000 | 0.231 | 436.768 |
| 23 | 934.186 | 11.000 | 0.216 | 590.201 |
| 24 | 293.173 | 6.000 | 0.067 | 290.441 |
| 25 | 767.649 | 10.000 | 0.177 | 250.751 |
| 26 | 1109.885 | 14.000 | 0.255 | 698.734 |
| 27 | 806.319 | 12.000 | 0.185 | 366.725 |
| 28 | 641.685 | 13.000 | 0.146 | 359.627 |
| 29 | 304.348 | 8.000 | 0.069 | 9.169 |

Table 4.3 (continued)

| | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|
| 30 | 323.909 | 10.000 | 0.072 | 104.112 |
| 31 | 149.026 | 8.000 | 0.032 | 15.867 |
| 32 | 198.382 | 10.000 | 0.042 | 333.368 |
| 33 | 306.402 | 8.000 | 0.069 | 42.509 |
| 34 | 376.655 | 13.000 | 0.084 | 396.317 |
| 35 | 181.866 | 10.000 | 0.039 | 334.626 |
| 36 | 332.173 | 8.000 | 0.075 | 64.657 |
| 37 | 531.210 | 12.000 | 0.120 | 280.865 |
| 38 | 188.106 | 7.000 | 0.042 | 39.575 |
| 39 | 310.943 | 7.000 | 0.072 | 166.267 |
| 40 | 100.163 | 6.000 | 0.022 | 241.941 |
| 41 | 672.240 | 12.000 | 0.153 | 632.223 |
| 42 | 285.187 | 11.000 | 0.063 | 455.556 |
| 43 | 118.850 | 7.000 | 0.026 | 40.850 |
| 44 | 129.907 | 8.000 | 0.028 | 56.025 |
| 45 | 91.263 | 6.000 | 0.020 | 142.001 |
| 46 | 211.108 | 6.000 | 0.048 | 161.167 |
| 47 | 70.587 | 4.000 | 0.015 | 107.501 |
| 48 | 32.538 | 6.000 | 0.006 | 68.533 |
| 49 | 31.909 | 4.000 | 0.006 | 81.118 |
| 50 | 14.983 | 4.000 | 0.002 | 32.701 |
| 51 | 14.211 | 6.000 | 0.002 | 31.700 |
| 52 | 28.395 | 7.000 | 0.004 | 252.549 |
| 53 | 20.661 | 8.000 | 0.003 | 137.975 |
| 54 | 37.895 | 9.000 | 0.006 | 264.441 |
| 55 | 55.540 | 9.000 | 0.010 | 324.250 |
| 56 | 100.292 | 4.000 | 0.022 | 117.767 |
| 57 | 87.519 | 2.000 | 0.020 | 0.000 |
| 58 | 778.527 | 9.000 | 0.180 | 308.620 |
| 59 | 76.413 | 6.000 | 0.016 | 82.004 |
| 60 | 176.343 | 7.000 | 0.039 | 179.258 |
| 61 | 242.676 | 10.000 | 0.054 | 294.298 |
| 62 | 143.862 | 10.000 | 0.030 | 309.202 |
| 63 | 75.300 | 7.000 | 0.015 | 170.000 |
| 64 | 116.525 | 8.000 | 0.025 | 318.330 |
| 65 | 48.957 | 6.000 | 0.010 | 87.933 |
| 66 | 22.946 | 4.000 | 0.004 | 63.542 |
| 67 | 38.226 | 4.000 | 0.008 | 86.560 |
| 68 | 25.451 | 4.000 | 0.005 | 66.692 |
| 69 | 60.361 | 5.000 | 0.012 | 99.025 |
| 70 | 82.044 | 5.000 | 0.018 | 0.000 |
| 71 | 82.044 | 5.000 | 0.018 | 0.000 |
| 72 | 43.450 | 4.000 | 0.009 | 0.000 |

Table 4.3 (continued)

| | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|
| 73 | 42.796 | 7.000 | 0.008 | 226.674 |
| 74 | 8.993 | 4.000 | 0.001 | 0.000 |
| 75 | 11.667 | 4.000 | 0.002 | 0.000 |
| 76 | 28.395 | 6.000 | 0.005 | 89.119 |
| 77 | 16.635 | 4.000 | 0.003 | 0.000 |
| 78 | 412.119 | 8.000 | 0.093 | 160.388 |
| 79 | 307.347 | 6.000 | 0.071 | 79.000 |
| 80 | 725.994 | 10.000 | 0.166 | 481.281 |
| 81 | 65.961 | 6.000 | 0.013 | 55.165 |

----------------------------------------
Running time: 00:00:01
Output generated: 07 Feb 15 14:33:46
UCINET 6.501 Copyright (c) 1992-2012 Analytic Technologies

### 4.2.1 Case Study 2 – General Discussion

The "Top Ten" nodes for each centrality measure are detailed in Table 4.4 below. The four major intersections identified in the feasibility study are labeled as node 1, 2, 3 and 23. These nodes consistently appear in the "Top Ten" most central intersections when the data was analyzed. Though not all of the intersections within the Tulane Avenue study appeared in the "Top Ten" under each centrality analysis category, all four intersections appeared in the "Top Ten" at least twice, with node 2 appearing in the "Top Ten" under all centrality measures. Nodes 1 and 23 were ranked in the "Top Ten" three times each.

Running the Eigenvector and Bonacich Power measures resulted in identical "Top Ten" intersection rankings. Betweeness and 2 Step Reach rankings were similar but did not match or include all of the same intersections as Eigenvector and Bonacich Power. This is network geography and traffic volumes between the various intersections.

The intersections used in the Tulane Avenue study are circled in red in Figures 4.3 and 4.4. Regarding these intersections, this indicates that the centrality measures correlate with existing methods to determine critical intersections or corridors for improvement. The intersections covered in the Tulane Avenue study are also important when looking at O-D demand. The roadway network in this area is adjacent to busy commercial areas and a hospital. As such, there could be high volumes of traffic both day and night. The Tulane Avenue study intersections also closely align with the nodes that the SNA study found central to the network. As such, SNA, the Tulane Avenue study, and O-D demand analysis appear to closely align on this case study.

Table 4.4 Centrality Values Summary and Rankings by Node for Second Case Study

| | **Bonacich Power** | | **2 Step Reach** | | **Eigenvector** | | **Betweeness** | |
|---|---|---|---|---|---|---|---|---|
| **Rank** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** |
| **1** | 1,124.78 | 2 | 14.00 | 13 | 0.25 | 2 | 698.31 | 26 |
| **2** | 1,115.99 | 1 | 14.00 | 26 | 0.25 | 1 | 632.16 | 41 |
| **3** | 1,083.89 | 26 | 13.00 | 7 | 0.24 | 26 | 589.51 | 23 |
| **4** | 1,055.45 | 20 | 13.00 | 28 | 0.24 | 20 | 573.47 | 13 |
| **5** | 1,024.44 | 3 | 13.00 | 34 | 0.23 | 3 | 480.50 | 80 |
| **6** | 1,007.25 | 5 | 12.00 | 1 | 0.23 | 5 | 465.30 | 7 |
| **7** | 995.41 | 21 | 12.00 | 2 | 0.22 | 21 | 455.46 | 42 |
| **8** | 957.12 | 22 | 12.00 | 9 | 0.22 | 22 | 436.62 | 22 |
| **9** | 902.01 | 23 | 12.00 | 10 | 0.20 | 23 | 434.86 | 20 |
| **10** | 896.48 | 6 | 12.00 | 14 | 0.20 | 6 | 422.69 | 2 |

### 4.2.2 Case Study 2 – Betweeness Centrality

Somewhat surprisingly, nodes 1, 2, 3, and 23 do not rank very high in the Betweeness centrality measures because these nodes are located at or near the center of the network. Upon in depth review of the traffic volumes within the network, it was determined that this corridor had large traffic volumes but smaller volumes than several other intersections. The corridor was congested and in need of improvements because the roadway was not designed to efficiently move the volume of traffic it was handling at the time of the study.

Nodes 26 and 41 have the highest ranking Betweeness centrality. A quick review of the traffic volumes connecting them to adjacent nodes, prove they directly carry high volumes of traffic. As such, they have high Betweeness centrality measures. Node 23, ranked third in Betweeness centrality, was the highest ranking node that was the focus of the feasibility study. Figure 4.3 depicts the Betweeness centrality measures for this case study.

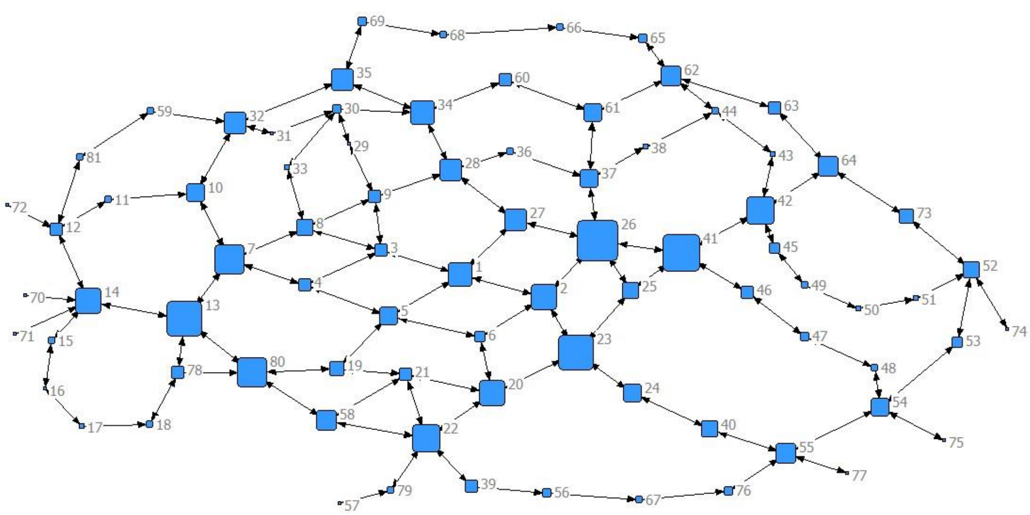



Figure 4.3 Network Betweeness Centrality Diagram for Second Case Study

### 4.2.3 Case Study 2 – Eigenvector Centrality

In the Eigenvector centrality measures, the nodes that are the focus of the feasibility study all appear in the "Top Ten" nodes of the network. This is logical as these nodes are connected to other nodes by high traffic volumes and because their immediate connections also have high volume connections to other nodes. These attributes lead to high Eigenvector centrality measures in nodes 1, 2, 3, and 23. Figure 4.4 depicts and details the Eigenvector centrality measures for Case Study 2.

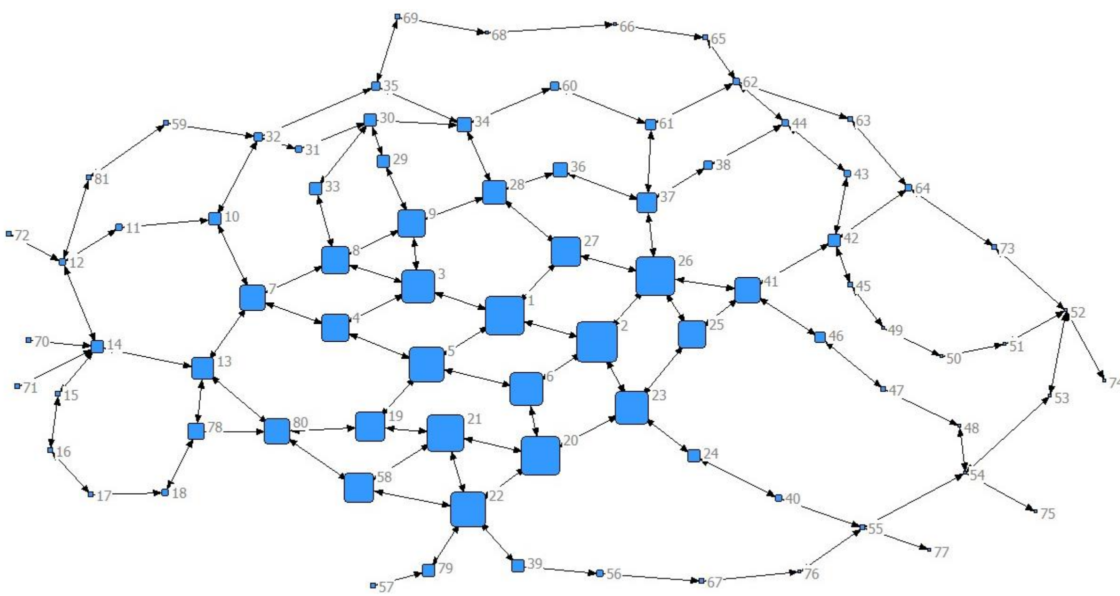



Figure 4.4 Eigenvector Centrality Diagram for Second Case Study

### 4.2.4 Case Study 2 – Bonacich Power

As with Case Study 1, the Bonacich Power centrality measures for Case Study 2 resulted in an identical rankings with Eigenvector centrality. As noted in Table 4.4, the high Bonacich Power centrality measure rankings indicate that the nodes located on the study corridor, are in general, “close” to the other nodes in the network. This ranking gives these nodes a high centrality ranking and power within the network.

### 4.2.5 Case Study 2 – 2 Step Reach

As noted in Table 4.4, the 2 Step Reach centrality ranked node 13 and 26 as the top ranked nodes for 2 Step Reach centrality measures. In reviewing the network layout, their high ranking is due to their immediate connection with five different nodes or their connection with a node that has four additional connections.

## 4.3 Case Study 3 – Shreveport Data Output

The centrality measures derived from the data generated for the Shreveport, LA case study are detailed in the Unicet output below (Table 4.5).

Table 4.5 Centrality Measures for All Nodes in Shreveport, LA Case Study

MULTIPLE CENTRALITY MEASURES

--------------------------------------------------------------------------------

| | |
|---|---|
| Input dataset: | Excel Model Final1 Dissertation (C:\School\Shreveport\Excel Model Final1 Dissertation) |
| Output dataset: | Excel Model Final1 Dissertation-cent (C:\Program Files (x86)\Analytic Technologies\Excel Model Final1 Dissertation-cent) |
| Treat data as: | Auto-detect |
| Type of scores to output: | Raw scores |
| Value of Beta was: | 0.277557500961711 |
| Principal eigenvalue was: | 3.58484276740862 |

Centrality Measures

| | Node | 1<br>BonPwr | 2<br>2Step | 3<br>Eigenvec | 4<br>Between |
|---|---|---|---|---|---|
| | | -------- | -------- | -------- | -------- |
| 1 | 1 | 176.940 | 11.000 | 0.022 | 317.259 |
| 2 | 2 | 213.313 | 12.000 | 0.028 | 479.706 |
| 3 | 3 | 296.221 | 12.000 | 0.067 | 451.790 |
| 4 | 7 | 120.410 | 9.000 | 0.016 | 302.948 |
| 5 | 9 | 17.392 | 4.000 | 0.002 | 99.399 |
| 6 | 10 | 87.527 | 10.000 | 0.007 | 435.894 |

Table 4.5 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 7 | 12 | 179.364 | 11.000 | 0.020 | 261.373 |
| 8 | 13 | 198.053 | 7.000 | 0.047 | 383.087 |
| 9 | 14 | 156.227 | 10.000 | 0.017 | 258.344 |
| 10 | 17 | 205.822 | 11.000 | 0.032 | 733.480 |
| 11 | 21 | 1461.375 | 16.000 | 0.356 | 1643.417 |
| 12 | 22 | 176.921 | 11.000 | 0.023 | 734.672 |
| 13 | 23 | 273.774 | 11.000 | 0.061 | 551.492 |
| 14 | 24 | 72.785 | 6.000 | 0.015 | 155.711 |
| 15 | 27 | 185.055 | 8.000 | 0.044 | 159.721 |
| 16 | 29 | 30.193 | 4.000 | 0.006 | 123.381 |
| 17 | 30 | 135.451 | 9.000 | 0.029 | 313.194 |
| 18 | 31 | 212.752 | 11.000 | 0.041 | 1202.210 |
| 19 | 32 | 225.130 | 11.000 | 0.043 | 1166.718 |
| 20 | 33 | 170.426 | 10.000 | 0.037 | 294.188 |
| 21 | 37 | 86.368 | 6.000 | 0.019 | 190.025 |
| 22 | 39 | 40.248 | 5.000 | 0.005 | 151.327 |
| 23 | 40 | 348.784 | 8.000 | 0.082 | 170.343 |
| 24 | 41 | 194.441 | 10.000 | 0.023 | 162.380 |
| 25 | 48 | 398.171 | 12.000 | 0.091 | 637.292 |
| 26 | 49 | 69.495 | 9.000 | 0.011 | 583.286 |
| 27 | A | 15.208 | 4.000 | 0.002 | 94.120 |
| 28 | B | 194.796 | 12.000 | 0.041 | 760.475 |
| 29 | C | 124.362 | 11.000 | 0.022 | 865.066 |
| 30 | E | 104.330 | 9.000 | 0.014 | 470.858 |
| 31 | F | 51.850 | 5.000 | 0.007 | 0.000 |
| 32 | G | 75.272 | 6.000 | 0.009 | 85.442 |
| 33 | H | 109.992 | 9.000 | 0.013 | 238.099 |
| 34 | I | 104.205 | 8.000 | 0.012 | 142.529 |
| 35 | J | 137.226 | 9.000 | 0.016 | 84.168 |
| 36 | K | 112.235 | 10.000 | 0.012 | 56.226 |
| 37 | L | 62.413 | 7.000 | 0.006 | 133.036 |
| 38 | N | 48.008 | 7.000 | 0.004 | 143.893 |
| 39 | O | 32.320 | 7.000 | 0.002 | 99.805 |
| 40 | P | 61.229 | 8.000 | 0.004 | 189.421 |
| 41 | Q | 69.438 | 9.000 | 0.005 | 260.963 |
| 42 | T | 38.268 | 6.000 | 0.002 | 0.000 |
| 43 | U | 54.996 | 9.000 | 0.006 | 445.609 |
| 44 | V | 57.387 | 9.000 | 0.010 | 460.101 |
| 45 | W | 32.374 | 6.000 | 0.005 | 36.450 |
| 46 | X | 52.046 | 8.000 | 0.008 | 207.058 |
| 47 | Y | 91.705 | 8.000 | 0.018 | 509.077 |
| 48 | Z | 52.627 | 10.000 | 0.006 | 137.006 |
| 49 | AA | 78.813 | 11.000 | 0.006 | 210.123 |

Table 4.5 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 50 | AB | 66.163 | 10.000 | 0.005 | 188.273 |
| 51 | AC | 62.184 | 10.000 | 0.005 | 189.265 |
| 52 | AD | 46.891 | 8.000 | 0.005 | 165.577 |
| 53 | AE | 168.284 | 10.000 | 0.027 | 632.952 |
| 54 | AF | 99.004 | 8.000 | 0.018 | 438.080 |
| 55 | AG | 234.206 | 10.000 | 0.051 | 515.799 |
| 56 | AH | 21.202 | 3.000 | 0.004 | 0.000 |
| 57 | AI | 59.798 | 7.000 | 0.012 | 26.667 |
| 58 | AJ | 615.939 | 11.000 | 0.148 | 627.704 |
| 59 | AK | 773.304 | 11.000 | 0.187 | 1013.674 |
| 60 | AM | 279.123 | 8.000 | 0.064 | 639.877 |
| 61 | AN | 266.046 | 7.000 | 0.062 | 558.546 |
| 62 | AO | 108.577 | 9.000 | 0.023 | 543.973 |
| 63 | AP | 280.014 | 12.000 | 0.065 | 780.538 |
| 64 | AQ | 39.066 | 4.000 | 0.008 | 1.000 |
| 65 | AR | 180.656 | 8.000 | 0.042 | 183.289 |
| 66 | AS | 614.644 | 12.000 | 0.149 | 1041.446 |
| 67 | AT | 308.915 | 9.000 | 0.074 | 195.864 |
| 68 | AU | 51.143 | 3.000 | 0.012 | 0.000 |
| 69 | AV | 761.546 | 12.000 | 0.185 | 397.066 |
| 70 | AW | 581.662 | 10.000 | 0.142 | 231.303 |
| 71 | AX | 1610.799 | 13.000 | 0.394 | 1313.044 |
| 72 | AY | 738.569 | 10.000 | 0.179 | 688.478 |
| 73 | AZ | 897.813 | 12.000 | 0.219 | 410.453 |
| 74 | BA | 608.988 | 9.000 | 0.149 | 132.854 |
| 75 | BB | 846.106 | 13.000 | 0.206 | 785.173 |
| 76 | BC | 333.651 | 7.000 | 0.080 | 48.833 |
| 77 | BD | 78.986 | 7.000 | 0.017 | 153.393 |
| 78 | BE | 141.917 | 8.000 | 0.032 | 341.337 |
| 79 | BF | 80.361 | 8.000 | 0.017 | 166.626 |
| 80 | BG | 23.305 | 3.000 | 0.005 | 0.000 |
| 81 | BH | 38.596 | 4.000 | 0.008 | 0.000 |
| 82 | BI | 66.006 | 4.000 | 0.014 | 0.000 |
| 83 | BJ | 55.067 | 4.000 | 0.011 | 0.000 |
| 84 | BK | 35.518 | 4.000 | 0.006 | 0.000 |
| 85 | BT | 260.207 | 8.000 | 0.062 | 203.821 |
| 86 | BU | 1063.083 | 11.000 | 0.260 | 257.733 |
| 87 | BV | 1224.108 | 11.000 | 0.300 | 303.681 |
| 88 | BW | 68.404 | 9.000 | 0.006 | 100.240 |
| 89 | BX | 292.625 | 8.000 | 0.069 | 256.394 |
| 90 | BY | 230.283 | 10.000 | 0.054 | 259.636 |
| 91 | BZ | 364.217 | 10.000 | 0.087 | 262.185 |
| 92 | CA | 341.150 | 10.000 | 0.081 | 528.107 |

Table 4.5 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 93 | CB | 113.501 | 9.000 | 0.025 | 209.864 |
| 94 | CC | 32.503 | 4.000 | 0.007 | 0.000 |
| 95 | CD | 51.368 | 6.000 | 0.011 | 27.869 |
| 96 | CE | 64.364 | 5.000 | 0.014 | 55.447 |
| 97 | CF | 173.319 | 8.000 | 0.041 | 207.281 |
| 98 | CG | 159.964 | 6.000 | 0.038 | 70.878 |
| 99 | CH | 90.563 | 6.000 | 0.021 | 82.720 |
| 100 | CI | 42.979 | 5.000 | 0.009 | 26.280 |
| 101 | CK | 61.434 | 8.000 | 0.005 | 155.990 |
| 102 | CL | 100.106 | 10.000 | 0.010 | 181.772 |
| 103 | CM | 104.185 | 11.000 | 0.011 | 554.523 |
| 104 | CN | 960.449 | 10.000 | 0.235 | 743.941 |
| 105 | CO | 222.393 | 6.000 | 0.054 | 32.131 |
| 106 | CP | 57.454 | 10.000 | 0.005 | 330.968 |
| 107 | CQ | 71.755 | 11.000 | 0.006 | 293.917 |
| 108 | CR | 55.220 | 10.000 | 0.006 | 282.606 |
| 109 | CS | 40.729 | 6.000 | 0.006 | 134.259 |

Table 4.5 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 110 | CT | 92.644 | 9.000 | 0.016 | 679.474 |
| 111 | CU | 1400.968 | 13.000 | 0.343 | 512.040 |
| 112 | CJ | 16.265 | 4.000 | 0.002 | 0.000 |

----------------------------------------

Running time: 00:00:05

Table 4.5 (continued)

Output generated: 07 Feb 15 10:32:45

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### 4.3.1 Case Study 3 – General Discussion

Traffic data and intersection rankings from a Shreveport, LA traffic report were utilized for this case study. Interestingly, few of the Shreveport, LA ranked intersections were ranked in the "Top Ten" nodes for the third case study (Table 4.6). The intersection ranked 21st in the traffic report was ranked first in two centrality measures. However, node AX was the overall highest ranking intersection in regards to centrality measures. It was ranked in the top four of each centrality measure. It is located near a major highway and adjacent to a commercial area, however, it was not one of the 50 busiest intersections determined by the City of Shreveport traffic engineering team.

Interestingly, Eigenvector and Bonacich Power rankings contained the same 10 intersections in the "Top Ten". However, the rankings of the top 5 intersections differed. This could be a result of the geographic location of the intersections. The layout of the highway network in the area created some separation and open areas within the network that impact the overall centrality and power of individual intersections.

After completion of the study, it was determined that few of the intersections with the highest traffic volume were ranked high in regards to centrality measures. For Shreveport, the highest ranked intersections in regards to centrality measures were generally centrally located within the network that was input into Unicet. Most of the intersections that had the highest traffic volumes/ranks in the Shreveport traffic engineering report are located on the periphery of the network, adjacent to large shopping centers and industrial areas. Because of their geographic location, it could be difficult for these nodes to receive high centrality ranks.

Table 4.6 Centrality Values Summary and Rankings by Node for 3rd Case Study

| | Bonacich Power | | 2 Step Reach | | Eigenvector | | Betweeness | |
|---|---|---|---|---|---|---|---|---|
| **Rank** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** |
| **1** | 1,400.97 | CU | 16.00 | 21 | 0.39 | AX | 1,643.42 | 21 |
| **2** | 1,224.11 | BV | 13.00 | AX | 0.36 | 21 | 1,313.04 | AX |
| **3** | 1,063.08 | BU | 13.00 | BB | 0.34 | CU | 1,202.21 | 31 |
| **4** | 1,610.80 | AX | 13.00 | CU | 0.30 | BV | 1,166.72 | 32 |
| **5** | 1,461.38 | 21 | 12.00 | 2 | 0.26 | BU | 1,041.45 | AS |
| **6** | 960.45 | CN | 12.00 | 48 | 0.24 | CN | 1,013.67 | AK |
| **7** | 868.82 | AZ | 12.00 | AP | 0.22 | AZ | 865.07 | C |
| **8** | 846.11 | BB | 12.00 | AS | 0.21 | BB | 785.17 | BB |
| **9** | 761.55 | AV | 12.00 | AV | 0.19 | AK | 780.54 | AP |
| **10** | 773.30 | AK | 12.00 | AZ | 0.19 | AV | 760.48 | B |

### 4.3.2 Case Study 3 – Betweeness Centrality

Figure 4.5 graphically depicts Betweeness centrality measures. Node 21 has the highest Betweeness centrality measure as noted in the Table 4.6. The superior size of node 21 in Figure 4.5 is much larger than the other nodes indicating it is a central intersection. As depicted in Figure 4.5, node 21 is connected to two other nodes that are ranked in the "Top Ten" Betweeness centrality measures. This is a strong indicator that this area of the network is located between many of the remaining network nodes.

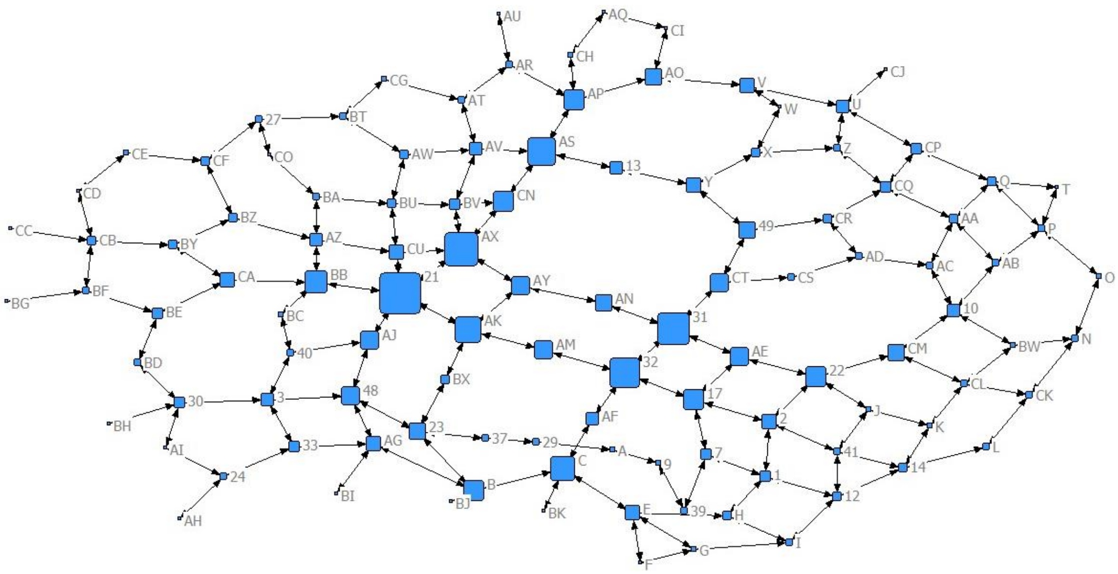


Figure 4.5 Network Betweeness Centrality Diagram for Third Case Study

### 4.3.3 Case Study 3 – Eigenvector Centrality

The Eigenvector centrality measures for the third case study revealed that only one Shreveport, LA traffic report ranked study was also ranked in the "Top Ten" (Table 4.6). This apparent discrepancy between the city rankings and the Eigenvector centrality measure rankings is likely due to the location of the intersections within the study. As noted in the general discussion for this study, many of the top ranked city intersections were towards the perimeter of the network, whereas, the intersections that are ranked in the "Top Ten" of the Eigenvector centrality measures are generally located in the interior of the network studied. Top ranked intersections are also generally located on major north/south and east/west travel corridors. In Figure 4.6, node AX is clearly the largest and most central to the network according to Eigenvector centrality measures.

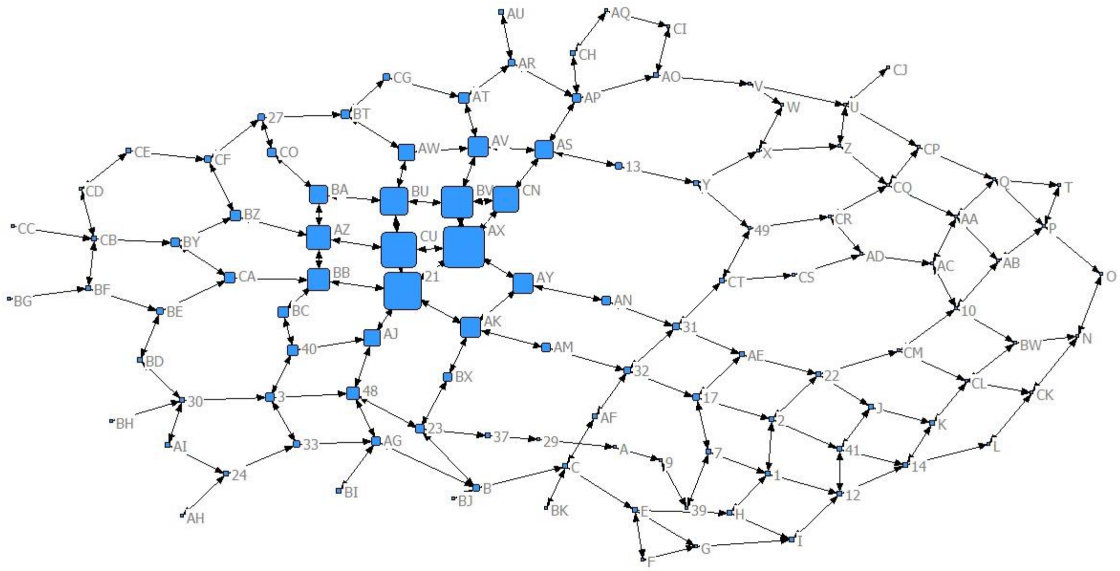


Figure 4.6 Eigenvector Centrality Diagram for Third Case Study

### 4.3.4 Case Study 3 – Bonacich Power

Unlike the previous two case studies, the ranking of the "Top Ten" nodes in the Bonacich Power centrality measures do not match the ranking of the nodes in the Eigenvector centrality measures. However, these two measures did rank the same 10 nodes in different orders. The three nodes ranked higher than node AX in Bonacich Power centrality rankings are all within two degrees it. These nodes are also located on major north/south and east/west travel corridors.

### 4.3.5 Case Study 3 – 2 Step Reach

2 Step Reach centrality measures ranked node 21 as the most central within the network. This measure also ranked two other Shreveport, LA traffic report ranked nodes in the "Top Ten". That being said, node 21 had 16 nodes within a 2 Step Reach, three nodes had 13 nodes within a 2 Step Reach, and six nodes had 12 nodes within a Two Step

Reach. The spread amongst the "Top Ten" nodes was narrow except for node 21 which was the top ranked node. The others had a close number of 2 Step Reach values indicating that the network is similarly connected throughout.

## 4.4 Case Study 4 – Jackson, MS Data Output

The centrality measures derived from the data generated for the Jackson, MS case study are detailed in the Unicet output below (Table 4.7).

Table 4.7 Centrality Measures for All Nodes in Jackson, MS Case Study

MULTIPLE CENTRALITY MEASURES

------------------------------------------------------------------------------

| | |
|---|---|
| Input dataset: | Jackson (C:\School\Jackson\Jackson) |
| Output dataset: | Jackson Data Output (C:\School\Dissertation\Unicet Data and Models\Jackson Data Output) |
| Treat data as: | Undirected |
| Type of scores to output: | Raw scores |
| Value of Beta was: | 0.305663503612875 |
| Principal eigenvalue was: | 3.2552136397685 |

Centrality Measures

| | 1<br>BonPwr<br>-------- | 2<br>2Step<br>-------- | 3<br>Eigenvec<br>-------- | 4<br>Between<br>-------- |
|---|---|---|---|---|
| 1 | 589.500 | 12.000 | 0.153 | 299.924 |
| 2 | 257.195 | 6.000 | 0.065 | 159.000 |
| 3 | 702.336 | 11.000 | 0.182 | 206.874 |
| 4 | 79.615 | 4.000 | 0.020 | 0.000 |
| 5 | 79.615 | 4.000 | 0.020 | 0.000 |
| 6 | 79.615 | 4.000 | 0.020 | 0.000 |
| 7 | 215.678 | 4.000 | 0.056 | 0.000 |
| 8 | 606.289 | 9.000 | 0.157 | 164.991 |
| 9 | 186.321 | 4.000 | 0.048 | 0.000 |
| 10 | 627.553 | 10.000 | 0.162 | 122.690 |
| 11 | 868.817 | 10.000 | 0.224 | 198.510 |
| 12 | 568.164 | 7.000 | 0.146 | 107.000 |
| 13 | 174.667 | 4.000 | 0.045 | 0.000 |
| 14 | 174.667 | 4.000 | 0.045 | 0.000 |
| 15 | 454.222 | 7.000 | 0.118 | 14.950 |
| 16 | 873.189 | 10.000 | 0.227 | 111.317 |
| 17 | 800.758 | 10.000 | 0.208 | 108.440 |

Table 4.7 (continued)

| | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|
| 18 | 959.246 | 9.000 | 0.249 | 261.391 |
| 19 | 1037.136 | 11.000 | 0.269 | 328.514 |
| 20 | 612.222 | 6.000 | 0.159 | 0.000 |
| 21 | 751.178 | 11.000 | 0.193 | 353.678 |
| 22 | 230.608 | 4.000 | 0.059 | 0.000 |
| 23 | 629.566 | 10.000 | 0.161 | 218.512 |
| 24 | 721.873 | 10.000 | 0.187 | 203.695 |
| 25 | 1057.336 | 11.000 | 0.275 | 167.157 |
| 26 | 886.298 | 10.000 | 0.231 | 61.517 |
| 27 | 664.942 | 10.000 | 0.172 | 157.829 |
| 28 | 679.396 | 9.000 | 0.176 | 101.688 |
| 29 | 747.177 | 9.000 | 0.193 | 45.521 |
| 30 | 886.416 | 9.000 | 0.229 | 191.155 |
| 31 | 764.322 | 10.000 | 0.196 | 298.488 |
| 32 | 506.571 | 6.000 | 0.131 | 0.000 |
| 33 | 429.520 | 10.000 | 0.108 | 252.707 |
| 34 | 329.148 | 8.000 | 0.081 | 105.757 |
| 35 | 278.917 | 7.000 | 0.069 | 30.474 |
| 36 | 576.805 | 12.000 | 0.145 | 282.821 |
| 37 | 547.137 | 11.000 | 0.138 | 296.250 |
| 38 | 168.240 | 4.000 | 0.042 | 0.000 |
| 39 | 280.687 | 9.000 | 0.069 | 186.067 |
| 40 | 86.796 | 3.000 | 0.021 | 0.000 |
| 41 | 274.540 | 10.000 | 0.066 | 323.567 |
| 42 | 418.354 | 14.000 | 0.102 | 408.333 |
| 43 | 358.578 | 11.000 | 0.087 | 250.400 |
| 44 | 301.921 | 8.000 | 0.074 | 180.783 |
| 45 | 93.286 | 4.000 | 0.023 | 0.000 |
| 46 | 93.286 | 4.000 | 0.023 | 0.000 |
| 47 | 110.604 | 4.000 | 0.027 | 0.000 |
| 48 | 145.665 | 6.000 | 0.035 | 106.000 |
| 49 | 51.656 | 3.000 | 0.012 | 54.000 |
| 50 | 16.789 | 2.000 | 0.004 | 0.000 |
| 51 | 84.917 | 4.000 | 0.020 | 0.000 |
| 52 | 101.134 | 8.000 | 0.023 | 204.000 |
| 53 | 49.784 | 5.000 | 0.010 | 159.000 |
| 54 | 16.217 | 4.000 | 0.003 | 0.000 |
| 55 | 16.217 | 4.000 | 0.003 | 0.000 |
| 56 | 16.217 | 4.000 | 0.003 | 0.000 |

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Running time:  00:00:01
Output generated:  07 Feb 15 15:15:00
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### 4.4.1 Case Study 4 – General Discussion

This case study analyzed the centrality of "primary arterial" streets in downtown Jackson, MS. The findings of the centrality analysis were generally what was expected. It was found that the most central intersections were in downtown Jackson or in higher traffic areas. In some locations, downtown Jackson roadways had lower traffic volumes than some of the outlying streets. This is likely a result of right of way and roadway width restrictions in the downtown area, as well as, more roadways to choose from within close proximity of a desired route. Streets towards the perimeter of the network were frequently spaced farther apart than downtown streets but they often carried higher volumes of traffic. Though they had a lower volume per individual street, there was a greater traffic volume density in the downtown Jackson area which resulted in higher overall centrality measures for the intersections located in this area.

The "Top Ten" rankings for Bonacich Power and Eigenvector contained the same 10 intersections with only two intersections ranked differently under the two measures. These intersections are generally concentrated in the downtown Jackson area. Betweeness and 2 Step Reach were more similar to each other than the other two measures. This is due to their non-scaled location, as well as, their geographic location within the overall network.

Table 4.8 below details the "Top Ten" rankings of the centrality analyses for the fourth case study. Figure 4.7 details the betweeness centrality of this network.

Table 4.8	Centrality Values Summary and Rankings by Node for 4th Case Study

| | Bonacich Power | | 2 Step Reach | | Eigenvector | | Betweeness | |
|---|---|---|---|---|---|---|---|---|
| **Rank** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** |
| **1** | 1,057.34 | 25 | 14 | 42 | 0.28 | 25 | 408.33 | 42 |
| **2** | 1,037.14 | 19 | 12 | 36 | 0.27 | 19 | 353.68 | 21 |
| **3** | 959.25 | 18 | 12 | 1 | 0.25 | 18 | 328.51 | 19 |
| **4** | 886.42 | 30 | 11 | 3 | 0.23 | 26 | 323.57 | 41 |
| **5** | 886.30 | 26 | 11 | 19 | 0.23 | 30 | 299.92 | 1 |
| **6** | 873.19 | 16 | 11 | 21 | 0.23 | 16 | 298.49 | 31 |
| **7** | 868.82 | 11 | 11 | 25 | 0.22 | 11 | 296.25 | 37 |
| **8** | 800.76 | 17 | 11 | 37 | 0.21 | 17 | 282.82 | 36 |
| **9** | 764.32 | 31 | 11 | 43 | 0.19 | 21 | 261.39 | 18 |
| **10** | 751.18 | 21 | 10 | 41 | 0.19 | 29 | 252.71 | 33 |

### 4.4.2 Case Study 4 – Betweeness Centrality

Figure 4.7 graphically depicts Betweeness centrality for Case Study 4. Upon review of this centrality measure is determined that node 42 has the highest Betweeness centrality in this network. Interestingly, based on distance, this intersection is not located in a high O-D demand area, however, it is located on a roadway with a high individual traffic count. Because traffic counts connected directly to a node greatly impact its Betweeness centrality measure, this high traffic count results in a high rank for node 42 and other nodes in the area. The downtown Jackson area is represented by three nodes in this centrality measure.

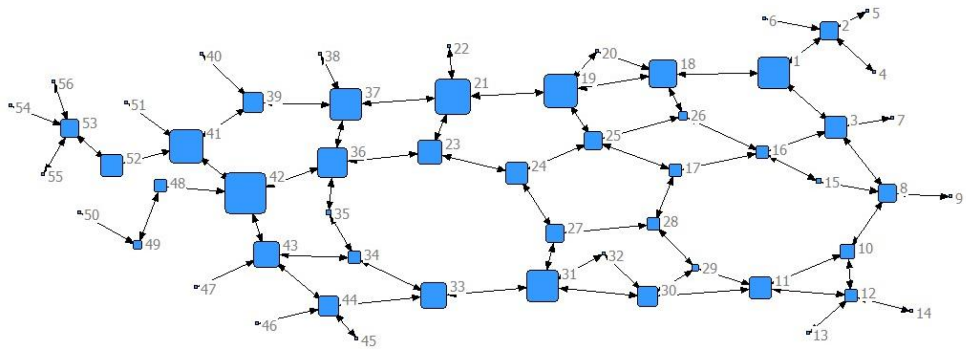


Figure 4.7 Network Betweeness Centrality Diagram for Fourth Case Study

### 4.4.3 Case Study 4 – Eigenvector Centrality

Figure 4.8 graphically depicts Eigenvector centrality for the Jackson case study. Intersections located in downtown Jackson are heavily represented in the "Top Ten" of this measures (Table 4.8). In fact, eight of the ten nodes in the "Top Ten" are located in downtown Jackson. The other two nodes are connected to nearly all downtown nodes by one or two degrees. This centrality ranking for downtown Jackson indicates that focus should be given to ensure that traffic congestion is controlled and mitigated in this area. Other areas should not be neglected but attention should be first given to these high centrality intersections first.

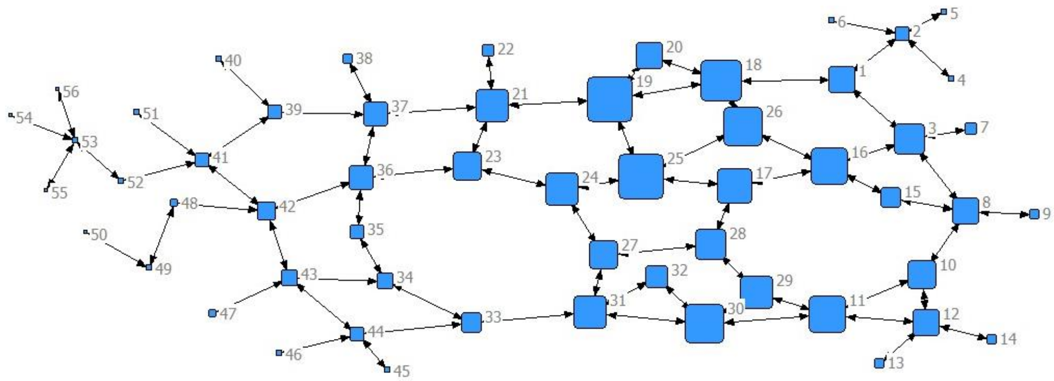


Figure 4.8 Eigenvector Centrality Diagram for Fourth Case Study

### 4.4.4 Case Study 4 – Bonacich Power

The "Top Ten" rankings for Bonacich Power centrality includes seven intersections that are geographically located in the downtown Jackson area. The intersections not located downtown are connected to intersections that are located downtown, indicating that the downtown area is a central transportation are in Jackson. This is logical as the downtown intersections carry fairly large volumes of traffic and have many connections nearby.

### 4.4.5 Case Study 4 – 2 Step Reach

The "Top Ten" rankings for the 2 Step Reach centrality measure tend to favor intersections located outside of downtown Jackson. During detailed review of the top ranking nodes, it was determined that these findings occurred because many of the downtown Jackson nodes had nodes within their 2 Step Reach paths that overlapped when tracing the routes. This overlap was caused by the tight spacing and geometry of the downtown roadway network. That being said, it resulted in lower 2 Step Reach centrality measures for downtown intersections. Because of the spacing between intersections and overall geometry of the network outside of the downtown area, node 42 had the highest 2 Step Reach centrality in this case study.

## 4.5 Case Study 4 – Mississippi Gulf Coast Network Data Output

The centrality measures derived from the data generated for the Jackson, MS case study are detailed in the Unicet output below (Table 4.9).

Table 4.9 Centrality Measures for All Nodes in Mississippi Gulf Coast Case Study

MULTIPLE CENTRALITY MEASURES

--------------------------------------------------------------------------------

| | |
|---|---|
| Input dataset: | Biloxi Data (C:\School\Biloxi\Biloxi Data) |
| Output dataset: | Biloxi Data-cent (C:\Program Files (x86)\Analytic Technologies\Biloxi Data-cent) |
| Treat data as: | Undirected |
| Type of scores to output: | Raw scores |
| Value of Beta was: | 0.317182587884423 |
| Principal eigenvalue was: | 3.13699429267256 |

Centrality Measures

| | Node | 1<br>BonPwr | 2<br>2Step | 3<br>Eigenvec | 4<br>Between |
|---|---|---|---|---|---|
| | | -------- | -------- | -------- | -------- |
| 1 | 1 | 11.999 | 2.000 | 0.002 | 0.000 |
| 2 | 2 | 34.678 | 4.000 | 0.007 | 116.000 |
| 3 | 3 | 106.129 | 3.000 | 0.024 | 0.000 |
| 4 | 4 | 91.027 | 6.000 | 0.020 | 344.000 |
| 5 | 5 | 212.977 | 8.000 | 0.049 | 855.026 |
| 6 | 6 | 110.910 | 6.000 | 0.025 | 352.392 |
| 7 | 7 | 82.183 | 6.000 | 0.017 | 178.776 |
| 8 | 8 | 92.187 | 6.000 | 0.020 | 47.000 |
| 9 | 9 | 507.854 | 8.000 | 0.121 | 149.904 |
| 10 | 10 | 460.069 | 8.000 | 0.110 | 1078.920 |
| 11 | 11 | 619.785 | 8.000 | 0.149 | 1404.680 |
| 12 | 12 | 869.886 | 9.000 | 0.210 | 61.067 |
| 13 | 13 | 484.765 | 6.000 | 0.117 | 34.995 |
| 14 | 14 | 541.409 | 8.000 | 0.130 | 167.907 |
| 15 | 15 | 779.758 | 11.000 | 0.187 | 418.935 |
| 16 | 16 | 315.472 | 7.000 | 0.075 | 122.495 |
| 17 | 17 | 1014.186 | 10.000 | 0.245 | 315.649 |
| 18 | 18 | 1050.465 | 10.000 | 0.254 | 616.830 |
| 19 | 20 | 873.771 | 10.000 | 0.211 | 972.758 |

Table 4.9 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 20 | 21 | 527.495 | 7.000 | 0.126 | 322.934 |
| 21 | 22 | 501.014 | 8.000 | 0.120 | 96.025 |
| 22 | 23 | 1167.368 | 13.000 | 0.281 | 1391.285 |
| 23 | 24 | 816.075 | 9.000 | 0.197 | 1603.513 |
| 24 | 25 | 776.277 | 8.000 | 0.186 | 1569.041 |
| 25 | 26 | 1075.879 | 12.000 | 0.258 | 1524.491 |
| 26 | 27 | 546.001 | 8.000 | 0.129 | 1964.959 |
| 27 | 28 | 722.569 | 11.000 | 0.171 | 2222.867 |
| 28 | 29 | 902.092 | 10.000 | 0.217 | 233.225 |
| 29 | 30 | 514.330 | 6.000 | 0.124 | 1.000 |
| 30 | 31 | 713.161 | 8.000 | 0.172 | 230.900 |
| 31 | 32 | 312.148 | 7.000 | 0.073 | 706.758 |
| 32 | 33 | 331.446 | 9.000 | 0.076 | 1714.832 |
| 33 | 34 | 206.812 | 9.000 | 0.043 | 1688.998 |
| 34 | 35 | 122.467 | 9.000 | 0.023 | 1106.333 |
| 35 | 36 | 97.351 | 7.000 | 0.016 | 1320.999 |
| 36 | 37 | 98.475 | 6.000 | 0.019 | 518.999 |
| 37 | 38 | 76.522 | 8.000 | 0.009 | 1338.165 |
| 38 | 39 | 97.414 | 9.000 | 0.007 | 1349.683 |
| 39 | 40 | 177.480 | 9.000 | 0.012 | 2813.684 |
| 40 | 41 | 74.118 | 6.000 | 0.010 | 1448.335 |
| 41 | 42 | 213.106 | 6.000 | 0.048 | 1801.169 |
| 42 | 43 | 119.564 | 6.000 | 0.022 | 1778.169 |
| 43 | 44 | 80.275 | 7.000 | 0.011 | 240.333 |
| 44 | 45 | 127.218 | 8.000 | 0.013 | 229.000 |
| 45 | 46 | 107.806 | 8.000 | 0.011 | 1482.501 |
| 46 | 47 | 88.141 | 6.000 | 0.008 | 116.000 |
| 47 | 48 | 28.957 | 3.000 | 0.003 | 0.000 |
| 48 | 49 | 112.254 | 7.000 | 0.010 | 148.000 |
| 49 | 50 | 129.093 | 9.000 | 0.010 | 1666.169 |
| 50 | 51 | 160.216 | 7.000 | 0.009 | 1261.500 |
| 51 | 52 | 160.216 | 7.000 | 0.009 | 1261.500 |
| 52 | 53 | 157.969 | 9.000 | 0.008 | 2516.000 |
| 53 | 54 | 32.420 | 4.000 | 0.001 | 0.000 |
| 54 | 55 | 99.059 | 10.000 | 0.004 | 2274.000 |
| 55 | 56 | 62.058 | 8.000 | 0.002 | 2036.000 |
| 56 | 57 | 20.683 | 3.000 | 0.001 | 0.000 |
| 57 | 58 | 66.452 | 8.000 | 0.001 | 1862.000 |
| 58 | 59 | 58.787 | 7.000 | 0.001 | 410.750 |
| 59 | 60 | 79.206 | 11.000 | 0.001 | 1327.167 |
| 60 | 61 | 49.929 | 9.000 | 0.000 | 421.167 |
| 61 | 62 | 24.314 | 5.000 | 0.000 | 106.167 |
| 62 | 63 | 20.423 | 5.000 | 0.000 | 3.000 |

Table 4.9 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 63 | 64 | 33.769 | 7.000 | 0.000 | 12.833 |
| 64 | 65 | 61.936 | 11.000 | 0.001 | 778.250 |
| 65 | 66 | 32.150 | 6.000 | 0.000 | 123.417 |
| 66 | 67 | 11.197 | 3.000 | 0.000 | 0.000 |
| 67 | 68 | 25.291 | 6.000 | 0.000 | 230.000 |
| 68 | 69 | 11.496 | 3.000 | 0.000 | 116.000 |
| 69 | 70 | 4.646 | 2.000 | 0.000 | 0.000 |
| 70 | 71 | 30.226 | 7.000 | 0.000 | 305.750 |
| 71 | 72 | 31.225 | 8.000 | 0.000 | 37.250 |
| 72 | 73 | 30.203 | 6.000 | 0.000 | 236.000 |
| 73 | 74 | 10.580 | 4.000 | 0.000 | 0.000 |
| 74 | 75 | 10.580 | 4.000 | 0.000 | 0.000 |
| 75 | 76 | 65.936 | 7.000 | 0.003 | 180.000 |
| 76 | 77 | 43.604 | 5.000 | 0.002 | 117.000 |
| 77 | 78 | 47.250 | 7.000 | 0.002 | 48.000 |
| 78 | 79 | 14.831 | 3.000 | 0.001 | 0.000 |
| 79 | 80 | 43.661 | 6.000 | 0.003 | 168.667 |
| 80 | 81 | 37.035 | 6.000 | 0.004 | 109.500 |
| 81 | 82 | 33.933 | 6.000 | 0.002 | 180.167 |
| 82 | 83 | 16.829 | 5.000 | 0.001 | 98.000 |
| 83 | 84 | 12.817 | 4.000 | 0.001 | 79.000 |
| 84 | 85 | 72.488 | 9.000 | 0.012 | 509.833 |
| 85 | 86 | 35.345 | 6.000 | 0.005 | 277.833 |
| 86 | 87 | 12.211 | 3.000 | 0.002 | 0.000 |
| 87 | 88 | 87.030 | 7.000 | 0.017 | 190.000 |
| 88 | 89 | 61.267 | 7.000 | 0.010 | 236.000 |
| 89 | 90 | 24.183 | 4.000 | 0.004 | 116.000 |
| 90 | 91 | 8.670 | 2.000 | 0.001 | 0.000 |
| 91 | 92 | 255.251 | 6.000 | 0.059 | 638.175 |
| 92 | 93 | 177.826 | 5.000 | 0.041 | 160.719 |
| 93 | 94 | 299.085 | 8.000 | 0.069 | 277.730 |
| 94 | 95 | 305.315 | 8.000 | 0.070 | 351.519 |
| 95 | 96 | 450.343 | 10.000 | 0.104 | 276.199 |
| 96 | 97 | 229.662 | 5.000 | 0.053 | 27.070 |
| 97 | 98 | 398.787 | 9.000 | 0.093 | 184.552 |
| 98 | 99 | 671.178 | 11.000 | 0.159 | 215.719 |
| 99 | 100 | 648.756 | 8.000 | 0.156 | 124.100 |
| 100 | 101 | 420.660 | 7.000 | 0.100 | 58.400 |
| 101 | 102 | 271.329 | 7.000 | 0.063 | 9.333 |
| 102 | 103 | 782.991 | 13.000 | 0.186 | 468.460 |
| 103 | 104 | 607.137 | 10.000 | 0.142 | 268.153 |
| 104 | 105 | 267.418 | 5.000 | 0.062 | 19.833 |
| 105 | 106 | 400.792 | 7.000 | 0.095 | 57.632 |

Table 4.9 (continued)

| | Node | BonPwr | 2Step | Eigenvec | Between |
|---|---|---|---|---|---|
| 106 | 107 | 650.158 | 9.000 | 0.154 | 409.720 |
| 107 | 108 | 311.988 | 7.000 | 0.074 | 221.621 |
| 108 | 109 | 327.160 | 8.000 | 0.077 | 257.711 |
| 109 | 110 | 208.540 | 8.000 | 0.048 | 121.779 |
| 110 | 111 | 130.391 | 8.000 | 0.029 | 305.509 |
| 111 | 112 | 29.872 | 3.000 | 0.006 | 0.000 |
| 112 | 113 | 27.067 | 3.000 | 0.006 | 0.000 |
| 113 | 114 | 202.154 | 8.000 | 0.046 | 159.642 |
| 114 | 115 | 17.276 | 5.000 | 0.002 | 102.000 |
| 115 | 116 | 608.266 | 9.000 | 0.146 | 322.434 |
| 116 | 117 | 668.429 | 8.000 | 0.161 | 264.294 |
| 117 | 118 | 46.936 | 9.000 | 0.000 | 242.833 |
| 118 | 119 | 44.435 | 8.000 | 0.000 | 114.417 |

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Running time: 00:00:01
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UCINET 6.501 Copyright (c) 1992-2012 Analytic Technologies

### 4.5.1 Case Study 5 – General Discussion

Study 5 focused on the coastal area of Mississippi. Centrality analysis determined that all critical intersections are located on or near the coast. Both Bonacich Power and the Eigenvector measure of centrality determined that nodes 23, 26, and 18 are the most critical intersections. Interestingly, none of these intersections is located on Highway 90 which carries consistently high volumes of traffic and connects the entire network area. They are also located in Gulfport, towards the west end of the network. It is interesting to note that the “Top Ten” for both of these measures are identical. The Betweeness and 2 Step Reach rankings differ substantially from the Bonacich Power and Eigenvector because of the geographic layout of the network in which there are several pinch points that create high Betweeness values. The “Top Ten” for each centrality measure are listed in Table 4.10 below.

Table 4.10 Centrality Values Summary and Rankings by Node for 5th Case Study

| | **Bonacich Power** | | **2 Step Reach** | | **Eigenvector** | | **Betweeness** | |
|---|---|---|---|---|---|---|---|---|
| **Rank** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** | **Unicet Value** | **Node** |
| **1** | 1,218.76 | 23 | 14 | 23 | 0.29 | 23 | 2,822.20 | 40 |
| **2** | 1,050.09 | 26 | 13 | 103 | 0.25 | 26 | 2,516.00 | 53 |
| **3** | 1,026.78 | 18 | 12 | 26 | 0.25 | 18 | 2,513.56 | 27 |
| **4** | 1,015.79 | 24 | 12 | 28 | 0.25 | 24 | 2,332.55 | 24 |
| **5** | 987.27 | 17 | 11 | 15 | 0.24 | 17 | 2,274.00 | 55 |
| **6** | 905.52 | 29 | 11 | 24 | 0.22 | 29 | 2,036.00 | 56 |
| **7** | 874.11 | 20 | 11 | 60 | 0.21 | 20 | 2,015.86 | 42 |
| **8** | 856.17 | 12 | 11 | 65 | 0.21 | 12 | 1,992.86 | 43 |
| **9** | 761.15 | 15 | 11 | 99 | 0.18 | 15 | 1,880.87 | 50 |
| **10** | 741.79 | 28 | 10 | 17 | 0.18 | 28 | 1,862.00 | 58 |

### 4.5.2 Case Study 5 – Betweeness Centrality

The Betweeness centrality measure determined that the top 3 intersections were located on Highway 90, directly adjacent to Gulf of Mexico. The Pascagoula area experienced some of the highest traffic volumes but they were confined to limited areas were commercial traffic is likely to travel. In Figure 4.9, nodes 40, 53, 24, and 56 are clearly the largest, indicating that they have the highest Betweeness centrality of the transportation network. Nodes 40 and 53 have the highest Betweeness centrality measures because they are located at at bottlenecks, meaning that all pathways must go through them to connect one side of the network to the other. They are essentially pinch points and earn a high betweeness ranking because of this fact. Other nodes in the network are in similar geographic positions but may have one additional connection which makes them slightly less between all nodes in the network.

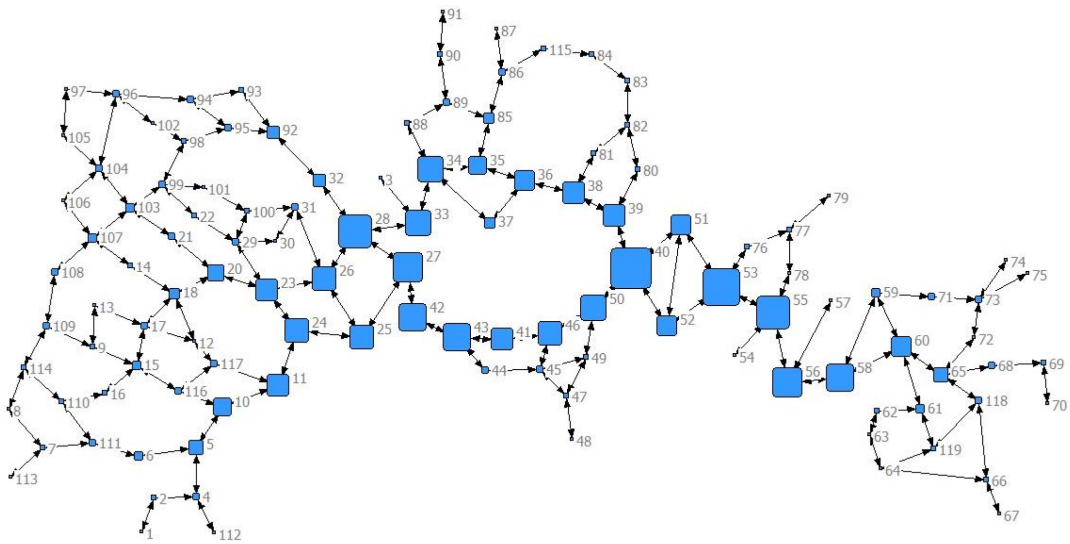


Figure 4.9 Network Betweeness Centrality Diagram for 5th Case Study

### 4.5.3 Case Study 5 – Eigenvector Centrality

As noted in the general discussion for Case Study 5, Eigenvector centrality measures indicate the network is skewed to the west, towards Gulfport. Upon review of traffic volumes and total population counts for Gulfport, Biloxi, and Pascagoula, the skewed appearance of Figure 4.10, mirrors these factors. Higher traffic counts were observed in the Gulfport area and Gulfport has the largest population of the three major cities included in this study. Gulfport's population is approximately 50% larger than Biloxi's and is nearly three times larger than the population of Pascagoula. Combining the populations of Biloxi and Pascagoula results in a number that is only slightly larger than Gulfport's individual population. As such, it makes logical sense and is demonstrated by the skewed layout of the network that Gulfport is the most central area according to Eigenvector centrality measures.

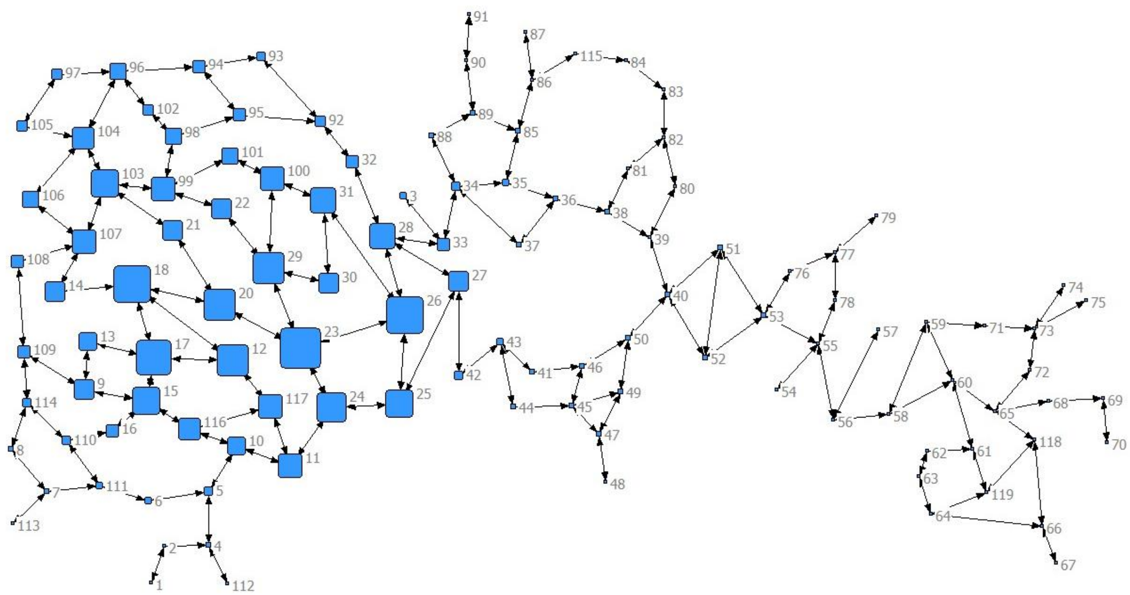

Figure 4.10 Eigenvector Centrality Diagram for Fourth Case Study

### 4.5.4 Case Study 5 – Bonacich Power

The "Top Ten" ranked nodes according to Bonacich Power centrality are the same "Top Ten" as for Eigenvector centrality. The Bonacich Power centrality measures rank these same Gulfport based nodes highly because there are generally a large number of high traffic count connections. Bonacich Power centrality gives nodes located in areas with high overall traffic counts, high centrality measures which results in the Gulfport nodes receiving high Bonacich Power centrality measures.

### 4.5.5 Case Study 5 – 2 Step Reach

Gulfport based nodes dominate the 2 Step Reach Centrality measures "Top Ten". Of the three sub-networks, Gulfport is the largest and best connected as noted in relevant figures and maps. This size and connectivity creates a situation where nodes have the ability to connect with large numbers of nodes within two steps of their position. As such, the west side of this study has large numbers of nodes ranked in the “Top Ten” of the 2 Step Reach centrality measures. This skews the 2 Step Reach Centrality measures to the west and to Gulfport.

### 4.6 Results Comparison

It should be noted that in all of the studies, the Bonacich Power and Eigenvector results were similar or identical for the “Top Ten” ranked intersections. This somewhat interesting as Bonacich Power utilizes power of an intersection as part of the calculation in determining the intersection rank. Knowing that power is partly determine by how much the adjacent nodes depend on the focus node for a relationship, it could be assumed that Bonacich Power would be a hybrid ranking or sorts, not matching Eigenvector Centrality, Betweeness, or 2 Step Reach. However, Bonacich Power and Eigenvector Centrality were identical or nearly identical in their “Top Ten” ranks for each study.

It is also noteworthy that 2 Step Reach and Betweeness differed substantially in their “Top Ten” ranks from the Bonacich Power and Eigenvector Centrality rankings. Intersections ranking high in Betweeness were often found at pinch points, sometimes in the central geographic area of the study, but did not rank high in other categories.

What this means for decision makers is that, assuming the network is complete with no holes or closures, intersections with high Bonacich Power and Eigenvector Centrality ranks are the most central and critical to the network. As such efforts should be focused on improving network capabilities in these areas. However, this assumes that pinch points do not become a hindrance and that there are no holes or closures in the network. For example, a bridge may not rank high on Bonacich Power and Eigenvector Centrality measures but could be ranked very high in 2 Step Reach or Betweeness measures. Ranking high in Betweeness measures means that it is used more than any other intersection in travelling from one intersection to another in the network.

For instance, in the Mississippi Gulf Coast Study, intersections west of the bay bridge were required to use the bay bridge to reach intersections on the east side. Without this relationship, these nodes are not connected in the network. This type of situation results in a high Betweeness ranking for bridges, pinch points, and other links in networks.

What this means for this and other similarly networks is that if one of the "Between" intersections is removed, traffic must make significant detours, directly impacting many other intersections. For infrastructure agencies, these findings indicate that high ranking Bonacich Power and Eigenvector Centrality intersections should be studied to improve daily commutes that involve large volumes of traffic.

Regarding Betweeness and 2 Step Reach, these measures can be used to identify intersections and relationships that have minimal or no redundancy. Locating these types of intersections for preparation and closure prevention during times of disaster or emergency is critical and these measures can help decision makers identify critical locations.

# CHAPTER V

# CONCLUSIONS AND FUTURE WORK

## 5.1 Conclusions

Based on the results of this research, it is shown that using social network analysis is a viable traffic congestion management tool, worth further and more in depth study. Proven successful in real world situations, using social network analysis will create a new perspective for evaluating traffic congestion and making related infrastructure network decisions. It will help decision makers determine critical intersections to focus research and decision making on.

In the CFI study, the model helped determine the exact areas for infrastructure improvement. Just as the LADOTD report focused on node 11, the research zeroed in on node 11 as one of the most critical and important intersections for congestion improvement.

In the Tulane Avenue study performed by the New Orleans Regional Planning Commission, the four intersections within the study area frequently earned high levels of centrality measures and power when utilizing SNA methods to analyze the transportation network. They ranked highly in all four major centrality measures. Combined, this indicates that the Tulane Avenue area is important to maximizing the traffic performance within the downtown New Orleans area. Improving this section of the network should be among the priorities for evaluating and improving the surface street transportation network in downtown New Orleans.

Case Study 3 which occurred in Shreveport, LA determined that intersections not listed in The City of Shreveport's "Top 50 Intersections Ranked by Volume" Report often play central roles in the overall network. This is because these intersections are located in key locations where any change to their capacity or congestion causing/mitigation abilities will have a large impact on the overall network. This is because of the geographic layout of the network where the intersections ranked highly by Shreveport's Report allow for easy route adjustments when changes to the traffic flow or congestion occur. In the other unranked intersections, many of which received high centrality measures, if they experience changes to traffic flow or congestion, there are few viable alternatives for network users to utilize.

The findings for the Jackson, MS case study were relatively straight forward. Generally, downtown Jackson intersections received high centrality measures when performing SNA on the traffic data. There were some intersections on the perimeter of the downtown Jackson area that earner high centrality measures. Interestingly, these rankings can be generally explained by the spread out nature and high traffic volumes of the intersections on the perimeters. Because there was less overlapping connectivity, these intersections were connected to a larger number of intersections which created higher centrality measures.

Three of the four centrality measures for the Mississippi Gulf Coast Case Study found that a large number of intersections in the Gulfport area were central to the network. This is largely due to the larger permanent population base being located in

Gulfport. Betweeness centrality found that an intersection located in nearly the center of the network, between all other nodes, had the highest Betweeness centrality measures. Specifically, intersections located in areas where they are isolated by fewer other intersections and relationships had the highest ranked betweeness centrality measures.

As noted in the Section 4.6 of this work, Bonacich Power and Eigenvector Centrality measures are most useful in identifying the most central and critical intersections in the day to day operation of the network. This is because they generally track higher traffic volumes and are similar to O-D demand studies where travel patterns of people are identified. They can help decision makers identify critical intersections and relationships for changes to improve performance and reduce congestion in the overall network. Improving these intersections and relationships will likely have smaller individual impacts but large cumulative network impacts when congestion reduction for each user is included.

2 Step Reach and Betweeness are also important factors. They are less useful in day to day operations and more useful in emergency planning or disaster prevention efforts. This is because they help identify intersections and relationships that have little to no redundancy, meaning, if those intersections or relationships fail, great impacts to the entire network will occur. When an event occurs at one of these intersections or relationships, the impact is fast and great to the overall network, often requiring days or months to remedy.

Using this model, design, construction and funding resources can be focused on the most critical intersections, getting more out of existing transportation infrastructure networks and pinpointing areas requiring modified infrastructure while helping to ensure that overreaction to congestion does not result in unnecessary construction efforts.

This model may also be able to help identify intersections that are not typically given a high priority when making infrastructure decisions. Because this method took much less time than traditional congestion or O-D demand studies, it could be very useful upon additional upon additional validation through additional case study work. This model could help transportation planners develop innovative solutions to infrastructure dilemmas.

Utilizing this model, finite resources can be focused on the areas that need improvement and that which improvement will have the biggest positive impact on the entire network. Sustainability will be increased through maximizing the traffic flow capacity of already in place infrastructure and by minimizing monetary and natural resource use to modify or add infrastructure.

Given that budgets for many individuals and organizations are limited do to current economic conditions, minimizing the money required to reduce traffic congestion is of utmost importance. Heightened awareness of environmental impacts of various aspects of life, including, traffic congestion and infrastructure modifications or additions, has also made maximizing the capabilities of existing infrastructure and minimizing the impacts of adding infrastructure critical.

Based on this first study and analysis, this model is worthy of additional study and real world validation to determine if it can supplement or replace traditional models in helping to reduce congestion. Doing this could improve the experience of the individual transportation network user and society as a whole. It has the potential to improve the lives of anyone who uses a transportation network.

## 5.2 Future Work

Future work should compare and validate this model against existing models, such as, O-D demand models. Doing this would ensure accuracy of this model in real world situations.

There are multiple other factors worthy of additional and more in depth study. Roadway geometry, signal timing, distances between intersections, geographic layout of the transportation network, data collection methods, and type of data collected should be evaluated in more detail. These factors will impact the centrality measures derived by utilizing SNA to identify central intersections for review during congestion management and mitigation. Roadway geometry will dictate how much traffic volume a roadway and handle prior to reaching congestion levels.

Signal timing can also impact travel time and network congestion. Certain intersections or roadway sections may appear congested if poor signal timing is implemented. Proper signal timing management will mitigate congestion where possible. As such, signal timing can impact roadway and intersection capacity within a network which could then impact the centrality measures of the network.

Distances between intersections could impact route selection and connectivity. Geographic layout will also impact network centrality measures. Roadway layout impacts how intersections are connected to other intersections and the routes utilized by network users.

Finally, data collection methods and the type of data utilized should be evaluated for improvement. Currently, traffic volumes taken at specific points in time are utilized for this work. This type of data does not always show a complete picture of a given section of the transportation network. All of the factors discussed above can impact the centrality of a network and deserve more study to ensure that they are properly accounted for when utilizing centrality measures to evaluate and improve traffic congestion within a network.

Currently, central intersections may be identified by utilizing this research model but there is not a definitive method to quantify congestion or delay based on a combination of centrality measures and other factors. As such, developing a method to quantify congestion based on centrality measures would be worthy of future research.

What-if scenarios should be performed. This means that alternative network layouts, traffic volumes, signal timings, and roadway geometries should be incorporated into the SNA data. Various scenarios could be played out to determine which scenario may best improve network congestion.

SNA of transportation networks could be integrated with developing SNA information for individual transportation network users. Multiple studies have begun to identify social networks and utilize these networks to identify and predict travel patterns. It is possible that these models could be integrated with the SNA model for the actual transportation network. Integrating these models would create a more holistic method for managing traffic congestion, improving the efficiency and sustainability of our complete transportation networks.

As the study requirements, comparisons, and validation discussed above take place, additional case studies should be undertaken. These studies could take place outside of Mississippi and Louisiana so that the case study and data sets could begin to be diversified more.

As more people are impacted by congestion in major metropolitan areas, future work should be focused on large areas. Metropolitan areas in the Southern United States that could benefit from this study are Atlanta and Dallas/Fort Worth. These cities have large volumes of single passenger car commuters. Cities like Los Angeles, Chicago, New York, etc. that have large and highly used mass transportation systems would also be good case study candidates. This is because a highly developed mass transit system has not been part of any of the networks studied to date. Mass transit stops and parking centers could impact network usage patterns, vehicular traffic flow, and congestion related delays.

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# APPENDIX A

# SUPPLEMENTAL DATA FILES

File Name: Baton_Rouge_Excel_Export

Date Created: 07/19/15

Description: Unicet traffic count data input

Created using: Unicet export to Excel

View using: Excel

File Name: New_Orleans_Excel_Export

Date Created: 07/19/15

Description: Unicet traffic count data input

Created using: Unicet export to Excel

View using: Excel

File Name: Shreveport_Excel_Export

Date Created: 07/19/15

Description: Unicet traffic count data input

Created using: Unicet export to Excel

View using: Excel

File Name: Jackson_Excel_Export

Date Created: 07/19/15

Description: Unicet traffic count data input

Created using: Unicet export to Excel

View using: Excel

File Name:  Biloxi_Excel_Export

Date Created:  07/19/15

Description:  Unicet traffic count data input

Created using:  Unicet export to Excel

View using:  Excel