Analyzing Traffic Layout Using Dynamic Social Network Analysis

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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 authors conducted social network analysis (SNA) using a two studies in Louisiana. Results indicate intersection SNA modeling aligns with current congestion studies and transportation planning decisions.</td></tr>
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ABSTRACT

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 authors conducted social network analysis (SNA) using a two studies in Louisiana. Results indicate intersection SNA modeling aligns with current congestion studies and transportation planning decisions.

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INTRODUCTION

Traffic congestion is a major problem in the United States. In ASCE's 2013 Roads Report Card, about 42% of major urban highways were congested (*2*). This congestion may be caused by a 39% increase in VMT with only a 4% increase in new construction road miles between 1990 and 2009 (*2*). Traffic congestion causes the following issues: reduced in travel speeds, restricted roadway capacity, unstable traffic conditions, increased fuel costs and length of travel times (*2*, *9*, *15*).

When delays occur, it is an indicator that a particular transportation network does not have a suitable design to meet the social and economic needs of current and future users. Increases in fuel consumption, engine emissions, vehicle wear and tear, and wasted time are caused by traffic congestion (*24*, *3*, *20*). Traffic jams have also detrimental effects on the physical and psychological well-being of commuters (*11*, *20*). In addition, high levels of speed reduction and travel time variability are dangerous to both the mental and physical safety of commuters. As a result, there are healthcare costs associated with bottlenecks and blockages. A study published by the National Institutes of Health (NIH) predicts the cost related to health impacts caused by congestion to be $13 billion by 2020 (*11*). Another negative cost effect of grid locked traffic is reduced economic productivity by limiting mobility of roadway users and commuters (*24*). In total, all negative impacts caused by traffic congestion, cost the economy $101 billion a year (*2*).

Transportation system users experience many of these effects on a regular basis. For many people, traffic congestion is a daily fact of life. A commute that takes 30 minutes in normal conditions may take 45 minutes to more than 60 minutes in bottle necked traffic conditions. Many roadway users are forced to deal with extended and variable commute times in order to travel to and from work, medical appointments, social events, etc. They deal with the negative effects of travel time delays without giving much thought to what congestion really is. They simply take familiar routes to arrive at their planned destinations. For example, when commuters can accurately predict the travel time of a desired route, it is likely that they will travel on that route (*15*). Transportation system users are hesitant to use untested travel networks to reach their planned destination because the travel time prediction of a new network can be less reliable than the time prediction of their regular travel network. They prefer to plan for extended and variable travel times than to plot different commute routes.

OBJECTIVE

The objective of this research is to help bridge the gap between engineering and social science disciplines. Attention is given to determine the applicability of social science to transportation studies. 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. To achieve this goal, the main objective of this project is to study the centrality of the existing road networks using social network analysis. As transportation networks are groups of related intersections and roadways, this SNA model can provide guidance for improving these relationships.

SCOPE

This work evaluated existing congestion identification and mitigation models. To mitigate traffic congestion several methods of evaluations have been developed to determine key traffic attributes and aid decision makers in transportation planning efforts. Origin-destination (O-D) demand, signal timing and geometry of intersections or roadways are some variables that can indicate that congestion will occur. These attributes provide guidance when designing new networks and redesigning in-place, congested transportation networks.

O-D demand is a critical component of the trip distribution calculation. During a typical trip distribution calculation, O-D demand is determined by assigning origin and destination pairs for transportation network user trips.

The accuracy of O-D calculations is affected by two uncertainty causing variables: route selection and traffic volume variability (*8*). 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.

A variety of O-D demand literature was reviewed for this work, however, no matter the focus of the literature, 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.

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 (*21*). 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 (*21*). This indicates that the majority of the roadway users are "commuters" with the remaining 40% of traffic being intercity, if not, interstate travelers (*21*). 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 (*19*). 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 (*19*). Increasing system flexibility, improves travel time reliability (*19*). While travel time reliability is increased, a network with a high level of flexibility may complicate the determination of route usage and congestion location.

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 (*8*). 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 (*8*). Research found that this demand model was accurate and within the required confidence intervals when applied an actual transportation network (*8*). 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 (*7*). Capacity reliability is the probability that a network, at a required service level, can meet the traffic volume demand requirements (*7*). 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 (7). 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 model based on the ultimate capacity and practical utility concepts were developed

(*7*). 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 (*7*).

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 (*7*). 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.

Another study 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 (*23*). 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 (*22*). 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 (*22*). 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 (*10*). 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 (*10*). Though not as high, there a correlation between predicted and actual travel time (*10*). 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 brief summary and comparison of relevant O-D demand literature is detailed below in Table 1. Blank boxes indicate a certain attribute was not studied in the literature, whereas, boxes filled with an “x” indicate that the selected literature studied that attribute.

Table 1. Summary & Comparison of O-D Demand Literature Review Findings

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.

Two factors that impact the travel time and traffic volume, 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 congestions because they are negatively impacted by skewness and downgrade (*18*). 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 (*12*). 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 (*12*). 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 (*12*). 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 (*14*). 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 (*16*).

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 (*4*). 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 (*1*). 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, even if it causes an out of sequence signal cycle. Giving transit vehicles signal priority can cause delay at the intersection and in the overall network, especially, as the number of transit vehicles increases (*16*).

Given the number of different variables and factors that contribute to high and low level performance of transportation networks, it is difficult and/or time consuming for existing models to make accurate predictions of traffic flow volumes, travel time and congestion. While it is known that commuters and the networks they use during their commute are relatively stable, developing a tool that utilizes social network analysis to examine the existing network and how to maximize its efficiency would be beneficial. This social network analysis tool can be used to analyze existing infrastructure to ensure that it is used efficiently and benefits individual commuters as well as the society as a whole. Specifically, individual commuters would benefit through reduced travel time and more reliable travel time predictions on a variety of transportation networks. Social network analysis of transportation networks could be used to identify critical locations for new or additional infrastructure expansion and construction. In addition, this tool could create a sustainable solution by focusing infrastructure expenditures on precise locations, reducing capital expenditures and reducing the use of finite resources in unneeded construction.

The scope of this project focuses on applying SNA to existing transportation networks and already completed transportation studies. Specifically, two different transportation networks are studied and analyzed using social network analysis tools. This research uses traffic data from the case studies as the base data for entry and analysis within the social network analysis framework. The results of applying social network analysis tools to transportation network study and analysis are presented. Specifically, Bonacich Power, 2 Step Reach, Eigenvector, and Betweeness Centrality are studied. Using the data presented in the case studies, new transportation network models are developed. These models consider the relationships and interactions of all intersections within the network.

METHODOLOGY

A total of 5 case studies were utilized for this report. Studies from Jackson, MS and the Mississippi Gulf coast were utilized for this work. One case study utilized information provided by the Shreveport, LA Public Works Department. Two case studies provided by the Louisiana Department of Transportation and Development (LADOTD) were utilized in this research. One case-study focused on a suburban intersection in Baton Rouge, LA. The second case-study focused on an urban street in New Orleans, LA. As such, this research focused on small world applications to simplify the social network analysis processes and calculations. Accordingly, the traffic network in a particular "neighborhood" area was studied instead of the entire city. In retrieving and analyzing related data, intersections within the networks under investigation were considered nodes and traffic flow between nodes was considered as flow or relation.

First Case Study

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 were 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) (*13*). Figure 1 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.

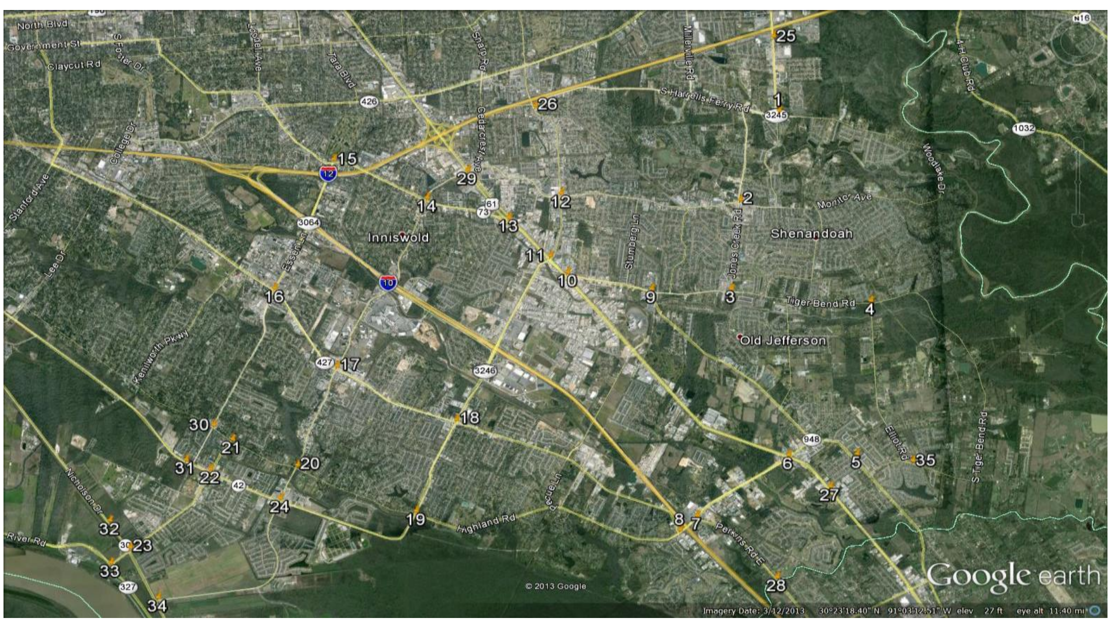

Figure 1. Baton Rouge Transportation Network Map – CFI Study

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. 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 were entered into a social network analysis program. The software selected for this research is Unicet 6.

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 of adjacent nodes (*6*). For this study, degree centrality is determined based on the total traffic volume that each node receives.

- 2 Step Reach – determines centrality by summing the number of other nodes within 2 steps/links of a particular node (*6*).

- Eigenvector – a closeness centrality measure that determines node centrality based on the closeness centrality of adjacent nodes (*6*). Closeness centrality is calculated by determining how many connections are required to connect a selected node to all other nodes. 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 (*6*).

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 with node size scaled based on centrality, were analyzed to gain a better understanding of where the "power" nodes were located. Strength of nodes and clusters can be easily determined using network images. These details are provided in the results and analysis section of this paper.

It was not possible to obtain specific signal timing information and data for this area. As such, it was not included with the discussion of the results.

Second Case Study

The second case study involved the Tulane Avenue Feasibility project in New Orleans, LA (*17*). 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 2 diagrams the area and layout of the intersections utilized. It was not possible to obtain specific signal timing information and data for this area. As such, it was not included with the discussion of the results.

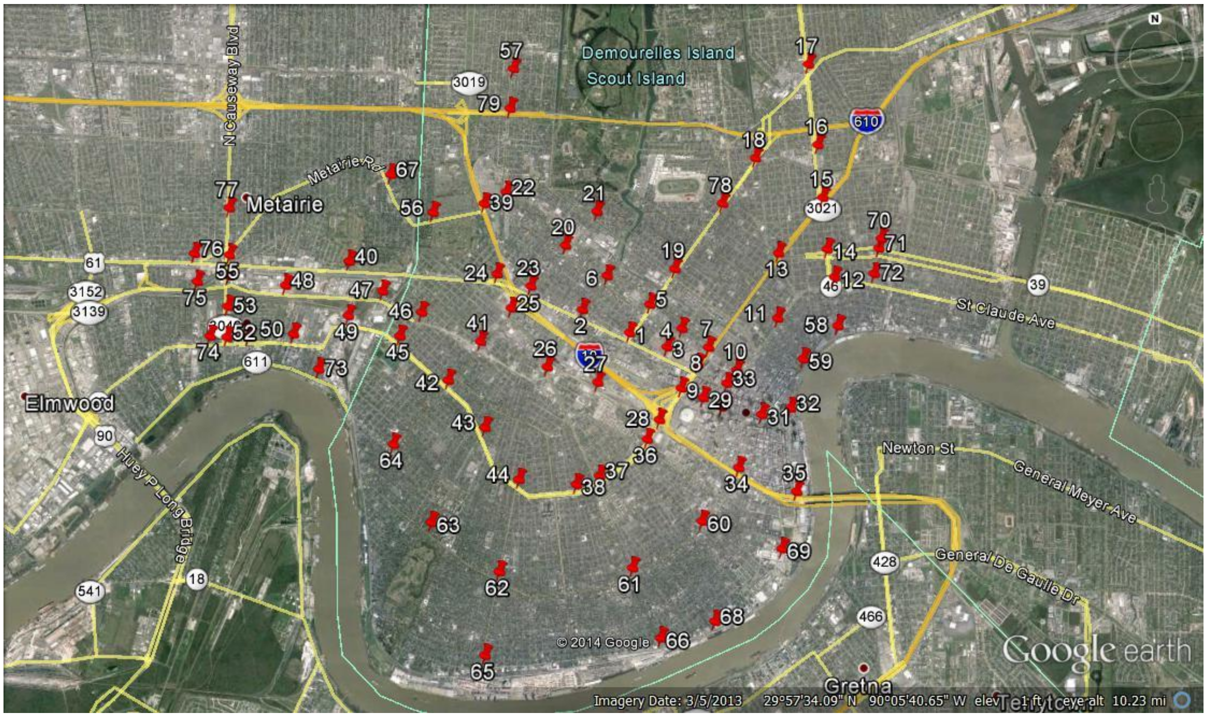

Figure 2. New Orleans Network Map & Layout for Second Case Study

Third Case Study

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 but used in this research were labeled with letters to differentiate between city ranked intersections and other intersections used for research purposes. Figure 3 details the layout of the intersections and the area utilized for this study. It was not possible to obtain specific signal timing information and data for this area. As such, it was not included with the discussion of the results.

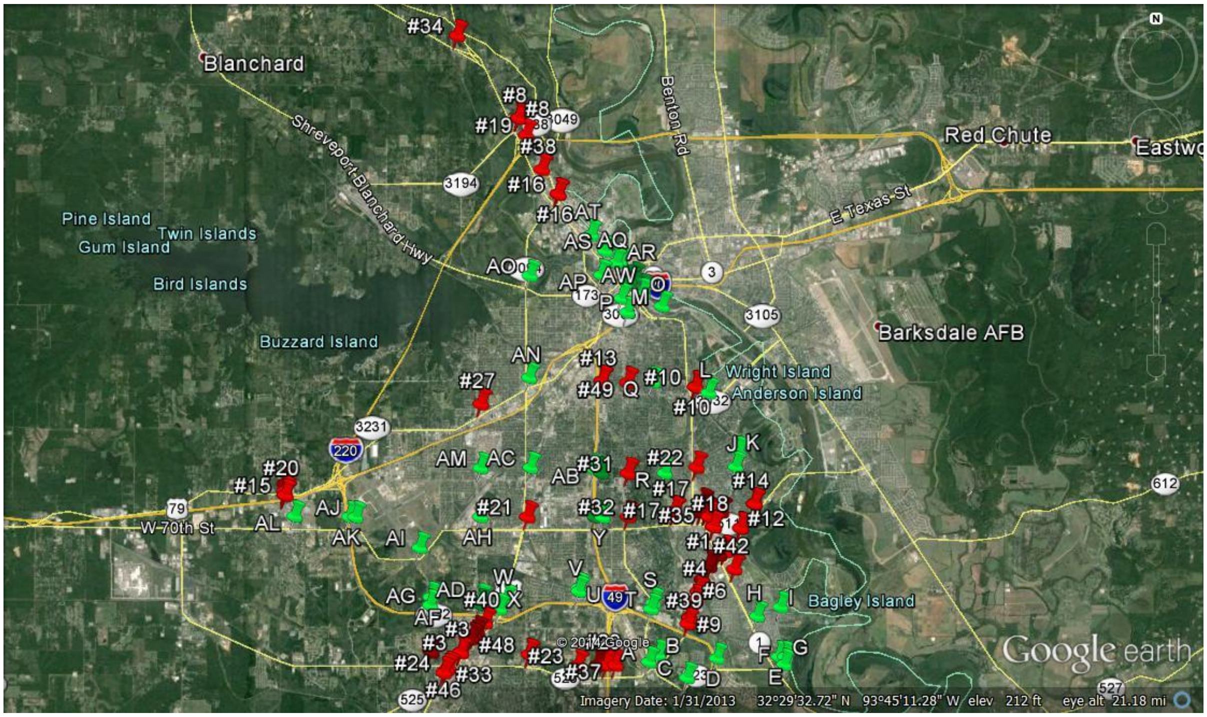

Figure 3. Shreveport Network Map & Layout for Third Case Study

Fourth Case Study

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 4 provides a map of the area within I-220, I-55, and I-20 that was utilized for this study. It was not possible to obtain specific signal timing information and data for this area. As such, it was not included with the discussion of the results.

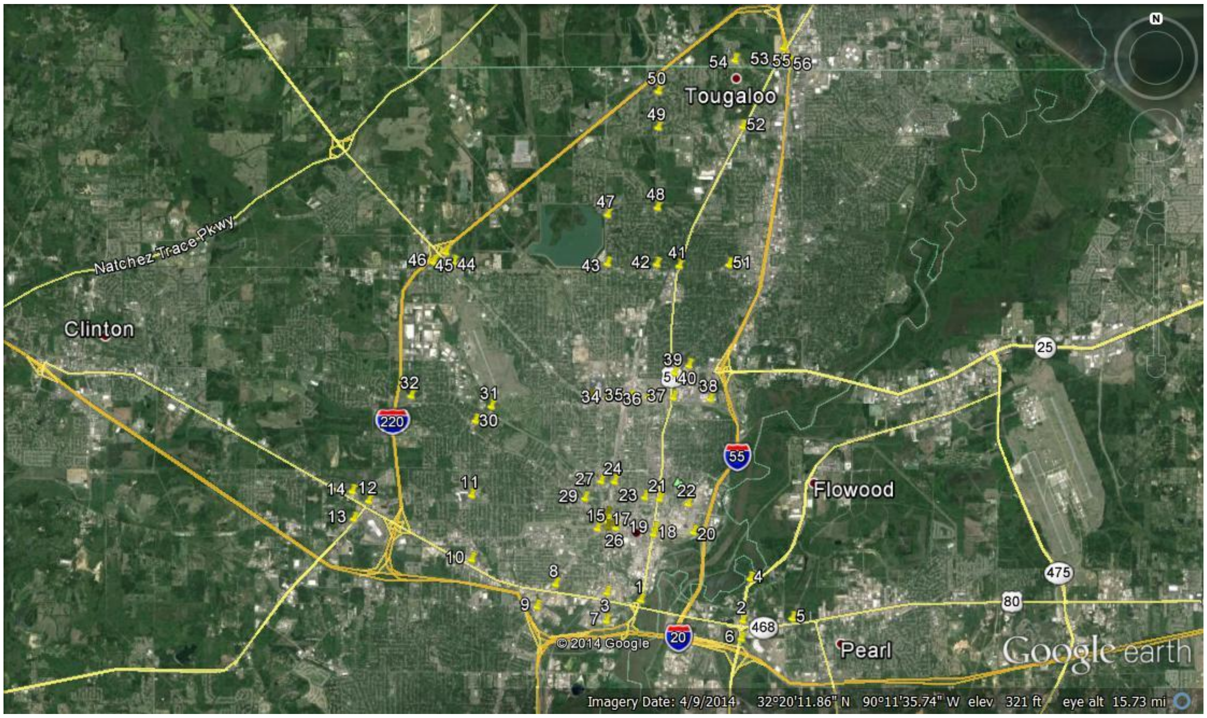

Figure 4. Jackson Network Map & Layout for Fourth Case Study

Fifth Case Study

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 5 details the Gulfport, Biloxi, and Pascagoula areas that were utilized for this study. It was not possible to obtain specific signal timing information and data for this area. As such, it was not included with the discussion of the results.

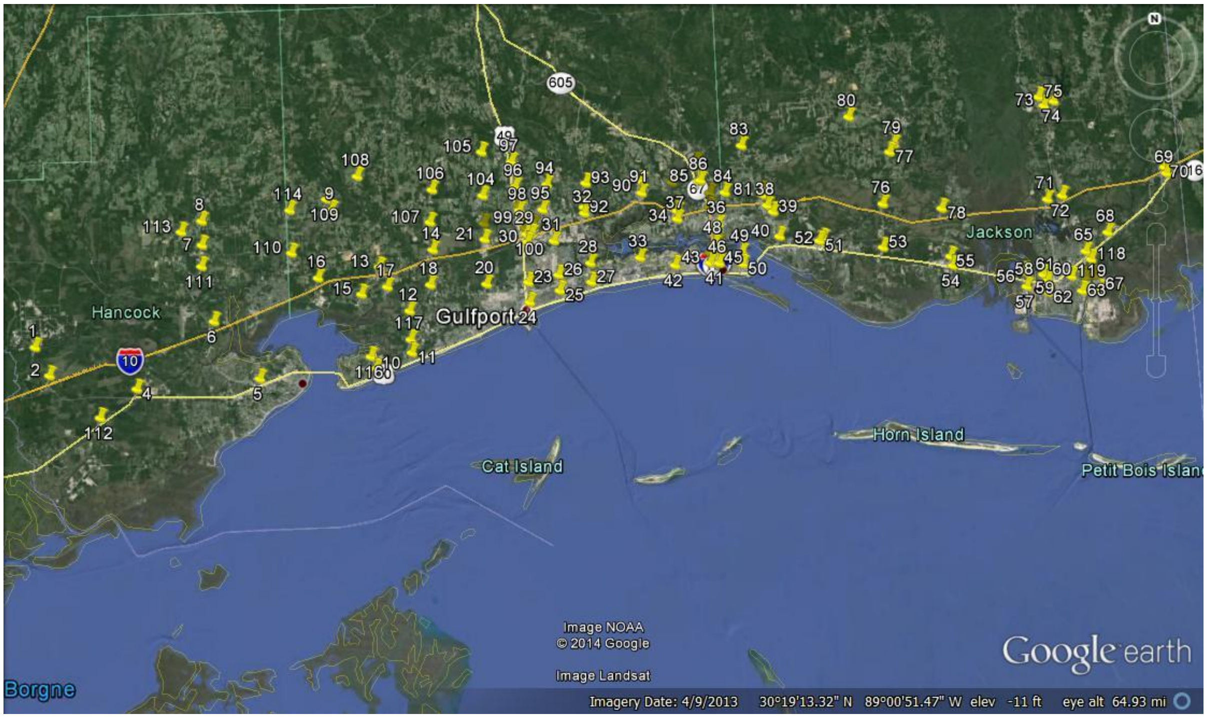

Figure 5. Mississippi Gulf Coast Network Map & Layout for Fifth Case Study

DISCUSSION OF RESULTS

The analysis of the CFI in Baton Rouge was compiled in a spreadsheet and is detailed in Table 2. Each node was ranked for each category of centrality studied. Node 11 and node 19 each ranked number one in two of the centrality measures. Table 1 provides the details and rankings for each of these categories and nodes. As shown in Figure 1, Node 11 was the CFI intersection of US 61 (Airline Highway) and LA 3246 (Siegen Lane). Interestingly, the traffic volume reported in the case study increased after the completion of construction of the CFI. 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.

The betweeness centrality is shown in Figure 6 where the top 10 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 on the edge of the network. In addition, node 11 is shown as the largest node in the network. 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 15 nodes to the right of node 11 and 19 nodes to the left of node 11, yet using betweeness centrality (as well as two other measures) as the analytical factor, node 11 is the most central node in the network.

Table 2. Centrality Values 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	1120.03	19	13.00	11	0.36	19	180.77	11
2	1073.38	20	13.00	17	0.34	20	159.02	18
3	1052.06	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

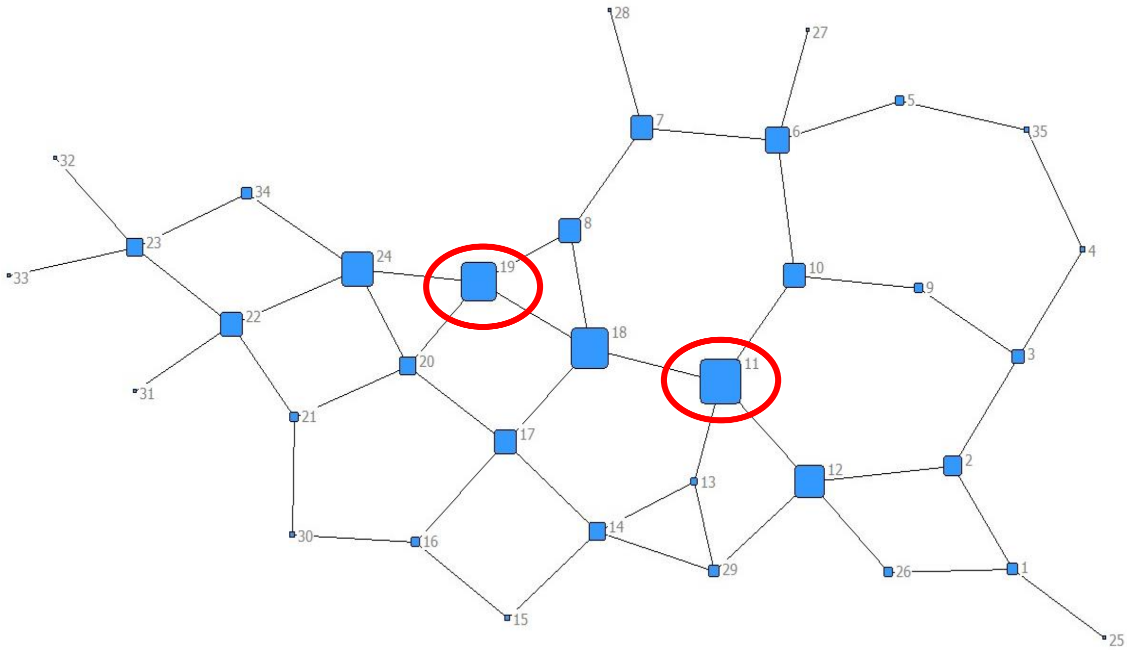

Figure 6. Network Betweeness Centrality Diagram for First Case Study

Table 3 details the analysis and findings of the Tulane Avenue network case study. The four major intersections within this study are represented by nodes 1, 2, 3 and 23. These nodes consistently appear in the top 10 most central intersections when the data was analyzed. Though not all of the intersections within the Tulane Avenue study appeared in the top 10 under each centrality analysis category, all four intersections appeared in the top 10 at least twice, with three intersections appearing in the top 10 for three centrality measures. Betweeness centrality is shown in figure 7.

Table 3. 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	1124.78	2	14.00	13	0.25	2	698.31	26
2	1115.99	1	14.00	26	0.25	1	632.16	41
3	1083.89	26	13.00	7	0.24	26	589.51	23
4	1055.45	20	13.00	28	0.24	20	573.47	13
5	1024.44	3	13.00	34	0.23	3	480.50	80
6	1007.25	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

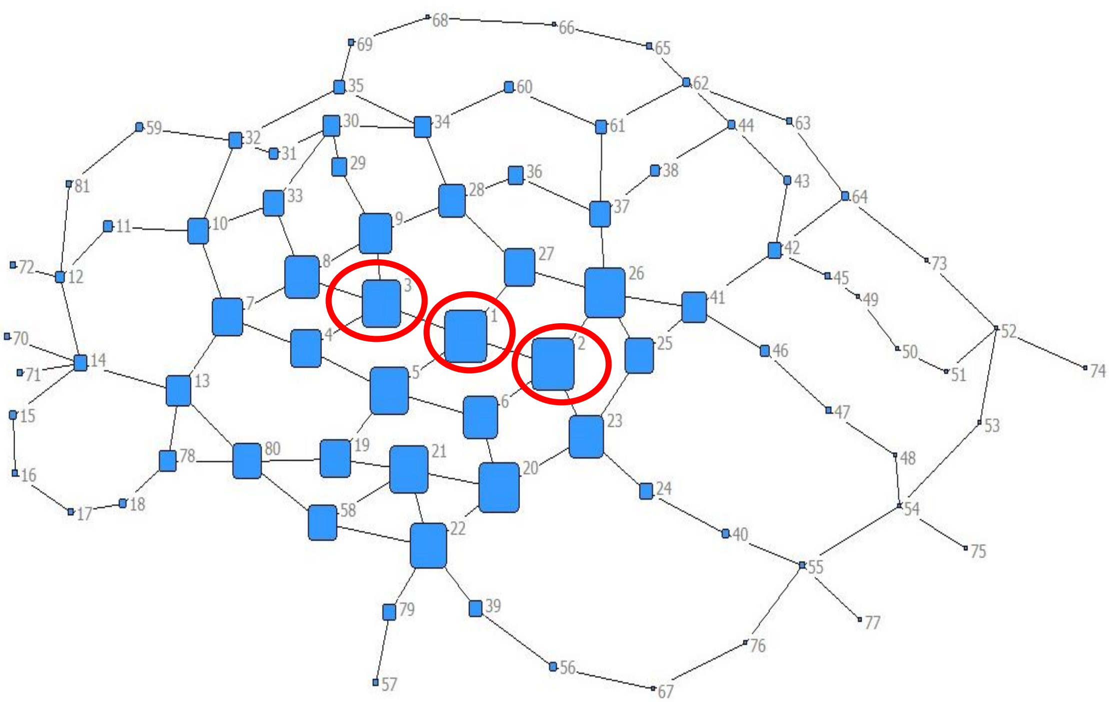

Figure 7. Network Betweeness Centrality Diagram for Second Case Study

It is interesting to note that the focus area of each of the previously discussed studies was ranked at the top or near the top of the centrality analysis. The intersections used in the Tulane Avenue study are circled in red. Regarding these studies, this indicates that 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 details the SNA findings for the third case study. Node AX was clearly the highest ranking intersection in regards to centrality measures. 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. 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. Figure 8 graphically depicts the betweeness centrality measures. Node 21 has the highest betweeness centrality measure as noted in table 4. The superior size of node 21 in Figure 8 is much larger than the other nodes indicating it is a central intersection. Regarding O-D demand, node AX does not appear to meet key O-D demand factors which would indicate it is a critical intersection. It is not located near destinations attracting large numbers of people and does not receive the highest volume of traffic.

Table 4. 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	1400.97	CU	16.00	21	0.39	AX	1643.42	21
2	1224.11	BV	13.00	AX	0.36	21	1313.04	AX
3	1063.08	BU	13.00	BB	0.34	CU	1202.21	31
4	1610.80	AX	13.00	CU	0.30	BV	1166.72	32
5	1461.38	21	12.00	2	0.26	BU	1041.45	AS
6	960.45	CN	12.00	48	0.24	CN	1013.67	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

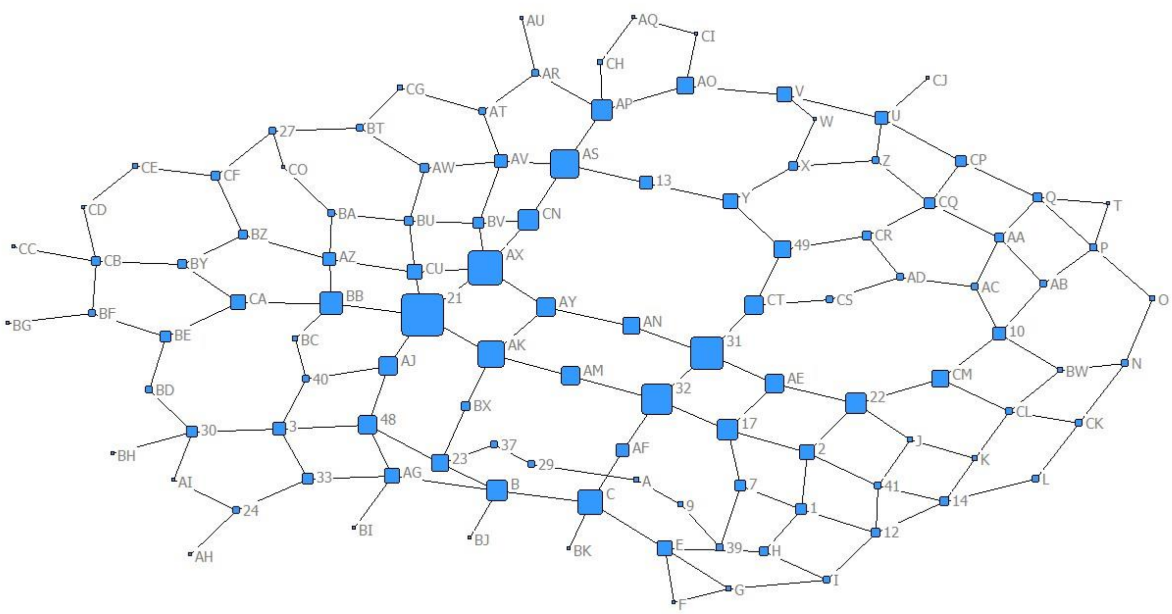

Figure 8. Network Betweeness Centrality Diagram for Third Case Study

The fourth case study conducted 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 high traffic areas. In some locations, downtown Jackson roadways had lower traffic volumes than some of the outlying streets. This is likely because there are more streets available for users to travel on in the downtown area. Streets towards the edge of the network were frequently spaced farther than downtown streets but they often carried higher volumes of traffic. This explains how both lower volume close proximity intersections and high volume distant intersections can be central to a network. Table 5 below details the findings of the centrality analysis for the fourth case study. Figure 9 details the betweeness centrality of this network. The size of node 42 clearly indicates that it has the highest betweeness centrality of the network studied. Interestingly, based on distance, this intersection is not located in a high O-D demand area because it is located outside of the downtown corridor and away from major highways and high traffic volumes.

Table 5. 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	1057.34	25	14	42	0.28	25	408.33	42
2	1037.14	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

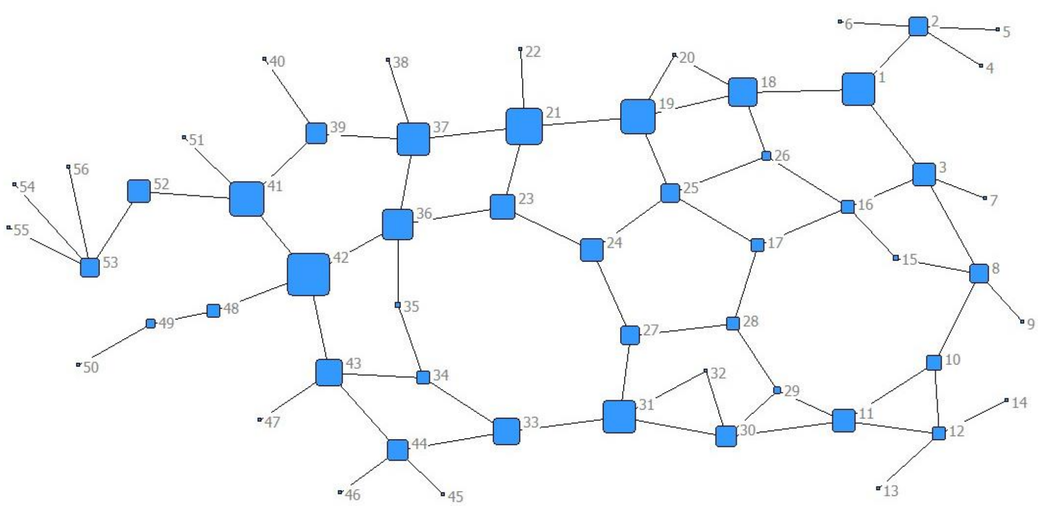

Figure 9. Network Betweeness Centrality Diagram for 4th Case Study

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. 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. Table 6 provides a complete summary of the centrality analysis done for this study. In figure 10, nodes 40, 53, 24, and 56 are clearly the largest, indicating that they have the highest betweeness centrality of the transportation network.

Table 6. 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	1218.76	23	13	103	0.30	23	2822.20	40
2	1050.09	26	12	26	0.25	26	2516.00	53
3	1026.78	18	11	28	0.25	18	2332.55	24
4	1015.79	24	11	15	0.25	24	2274.00	55
5	987.27	17	11	24	0.24	17	2036.00	56
6	905.52	29	11	60	0.22	29	2015.87	42
7	874.11	20	11	65	0.21	20	1992.87	43
8	856.17	12	11	99	0.21	12	1880.87	50
9	741.79	28	10	18	0.18	15	1862.00	58
10	740.73	103	10	17	0.18	103	1857.61	28

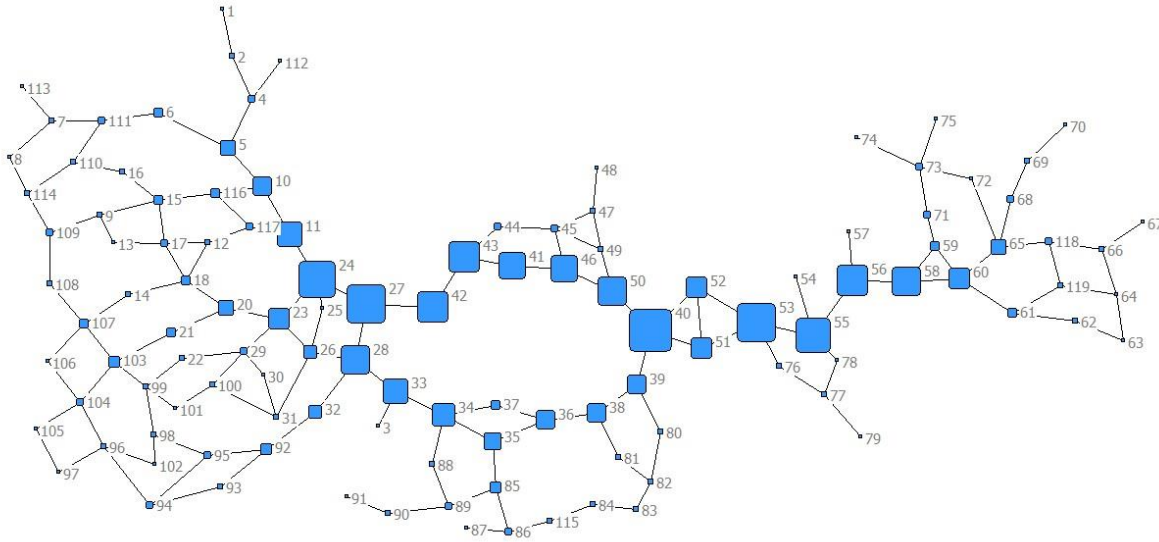

Figure 10. Network Betweeness Centrality Diagram for 5th Case Study

If an intersection is determined to have high centrality values within a network, it is an indicator that improving traffic volume capacity through it will have a high impact on mitigating congestion in the network as a whole. Interestingly, as indicated in the CFI study, traffic volume through an intersection may actually increase at a central intersection if its traffic volume capacity is improved, making the already central intersection, more central in its local network.

In case study 5, performing a more full review of the most central intersections could be very beneficial to network travel. This is because many of the central intersections are not experiencing high volumes of total traffic and could be expanded to help meet the overall network capacity needs.

CONCLUSIONS

Based on the results of this study, it is shown that using social network analysis is a viable traffic congestion management tool, worth further and more in depth study. Proven successful, 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. It zeroed in on node 11 as one of the most critical and important intersection for congestion improvement. In the Tulane Avenue study, the four intersections within the study area frequently earned high levels of centrality and power when analyzing the data. They ranked high in four different centrality measures. Combined, this indicates that the Tulane Avenue area studied is important to maximizing the traffic performance within the downtown New Orleans area. Improving this section of the network should be among the top priorities for improving the surface street transportation network in downtown New Orleans.

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. This model may be able to help identify intersections that are not typically given a high priority when making infrastructure decisions. Upon additional validation, this model could help transportation planners develop innovative solutions to infrastructure dilemmas. 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. This social network analysis model has the ability to improve the lives of all individuals currently affected by traffic congestion. Based on this first study and analysis, this model can be used to reduce congestion, improving many congestion related individual and society based factors. It has the potential to improve the lives of anyone who uses a transportation network.

RECOMMENDATIONS

Future work related this study should more fully address O-D distribution. The inherent nature of O-D distribution could have a large impact on network dynamics. It is hypothesized that areas with a high O-D distribution would also have a high centrality value. Future work should analyze networks in locations other than the southern United States. Population density, number of transportation options and the culture of the study area could change the results of the SNA analysis. In depth signal timing review and analysis should also be performed during follow-up research. Signal timing can impact traffic flow and route selection which influence total vehicular traffic volume. As such, signal timing could influence the results of roadway network analysis utilizing social network analysis. More complete traffic engineering data and research incorporation will provide better overall conclusions regarding the use of social network analysis to analyze traffic layout. However, upon further study and refinement of this research, it could be evaluated for use in a variety of transportation planning decisions.

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

ASCE	**American Society of Civil Engineers**
CFI	**Continuous Flow Intersection**
LA	**Louisiana**
LADOTD	**Louisiana Department of Transportation and Development**
NIH	**National Institute of Health**
O-D	**Origin-Destination**
SNA	**Social Network Analysis**
VMT	**Vehicle Miles Traveled**

REFERENCES

1. Ahmed, K., Abu-Lebdeh, G. and Al-Omari, B. "Estimation of Delay Induced by Downstream Operations at Signalized Intersections over Extended Control Time." Journal of Transportation Engineering, Vol 139, No. 1, 2013, pp 8-19.
2. American Society of Civil Engineers (2013). "2013 Report Card for America's Infrastructure." ASCE.
3. Antipova, A., Wilmot, C. "Alternative approaches for reducing congestion in Baton Rouge, Louisiana." Journal of Transport Geography, Vol. 24, 2012, pp 404-410.
4. Asante, S. "A Simulation Study of the Operational Performance of Left-Turn Phasing and Indication Sequences." Transportation Science, Vol. 30, No. 2, 1992, pp 112-119.
5. Borgatti, S.P. (2002). NetDraw: Graph Visualization Software. Harvard: Analytic Technologies.
6. Borgatti, S.P., Everett, M.G. and Freeman, L.C. (2002). Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies.
7. Chen, A., Kasikitwiwat, P., Yang, C. (2012). "Alternate capacity reliability measures for transportation networks." Journal of Advanced Transportation, Vol. 47, pp 79-104.
8. Chootinan, P., Chen, A. (2011). "Confidence interval estimation for path flow estimator." Transportation Research Part B, Vol. 45, pp 1680-1698.
9. Jun, J., Lim, I. "Potential Freeway Congestion Severity Measure: Impact of Continuous Congestion Patterns." Journal of Transportation Engineering, Vol. 135, No. 5, 2009, pp 316-321.
10. Lam, W., Chan, K., Shi, J. (2002). "A traffic flow simulator for short-term travel time forecasting." Journal of Advanced Transportation, Vol. 36, pp 265-291.
11. Levy, J., Buonocore, J., von Stackelberg, K. "Evaluation of the public health impacts of traffic congestion: a health risk." Environmental Health, Vol. 9, No. 65, 2010.
12. Liu, P., Lu, J., Zhou, H., Sokolow, G. "Operational Effects of U-Turns as Atlernatives to Direct Left-Turns." Journal of Transportation Engineering, Vol. 133, No. 5, 2007, pp 327-334.
13. Louisiana Department of Transportation and Development (2007). Continuous Flow Intersection (CFI) Report, US 61 (Airline Highway @ LA 3246 (Siegen Lane). LADOTD.
14. Perez-Cartagena, R. and Tarko, A. "Calibration of Capacity Parameters for Signalized Intersections in Indiana." Journal of Transportation Engineering, Vol. 131, No. 12, 2005, pp 904-911.
15. Pulugurtha, S., Pasupuleti, N. "Assessment of Link Reliability as a Function of Congestion Components." Journal of Transportation Engineering, Vol. 136, No. 10, 2009, pp 903-913.
16. Rahka, H. and Zhang, Y. "Sensitivity Analysis of Transit Signal Priority Impacts on Operation of a Signalized Intersection." Journal of Transportation Engineering, Vol. 130, No. 6, 2004, pp 796-804.
17. Regional Planning Commission for Jefferson, Orleans, Plaquemines, St. Bernard, and St. Tammany Parishes (2011). "US 61/Tulane Avenue Corridor Improvements Stage 0 Feasibility Report."
18. Sando, T. and Moses, R. "Influence of Intersection Geometrics on the Operation of Triple Left-Turn Lanes." Journal of Transportation Engineering, Vol. 135, No. 5, 2009,

pp 253-259.
19. Sofer, T., Polus, A., Bekhor, S. (2013). "A congestion-dependent, Dynamic Flexibility Model of freeway networks." Transportation Research Part C, Vol. 35, pp 104-114.
20. Traffic Congestion: Trends, Measures and Effects. Report PEMD-90-1 to the Chairman, Subcommittee on Transportation and Related Agencies, Committee on Appropriations, U.S. Senate, United State General Accounting Office, (1989).
21. Wang, M., Schrock, S., Vander Broeck, N., Mulinazzi, T. (2013). "Estimating Dynamic Origin-Destination Data and Travel Demand Using Cell Phone Network Data." International Journal of ITS Research, Vol. 11, pp 76-86.
22. Yang, H., Bell, M., Meng, Q. (2000). "Modeling the capacity and level of service of urban transportation networks." Transportation Research Part B, Vol. 34, pp 255-275.
23. Yim, K., Wong, S., Chen, A., Wong, C., Lam, W. (2011). "A reliability-based land use and transportation optimization model." Transportation Research Part C, Vol. 19, pp 351-362.
24. Zheng, S., Ahn, S., Monsere, C. "Impact of traffic oscillations on freeway crash occurrences." Accident Analysis and Prevention, Vol. 42, 2010, pp 6.