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Developing restoration schemes for a road transportation network in the event of a disaster

Ebin Antony

DEVELOPING RESTORATION SCHEMES FOR A ROAD TRANSPORTATION NETWORK IN THE EVENT OF A DISASTER

by

EBIN ANTONY

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Approved by:

Dr. Steven Corns, Advisor

Dr. Suzanna Long

Dr. Ruwen Qin

ABSTRACT

Transportation systems such as rail, road, and waterways are key component of critical infrastructure systems, providing connectivity between other components to enable the production and distribution of goods and services. During large scale disasters such as earth quakes and floods, this connectivity is disrupted, restricting or completely halting the flow of goods and services. To ensure that the connectivity between the different modes of transportation are restored in an aftermath of these disruptions, the interdependence between them and the importance of individual elements to the overall connectivity have to be studied and formulated to develop a system-level restoration plan. This paper presents a framework to develop efficient restoration schemes for a road transportation network in an aftermath of a disruption. The road transportation network is modelled using graph theory analytics. Using a system oriented parameter such as the Eigen-vector centrality measure associated with the road transportation, it is possible to understand the importance of different network components. This model captures the interdependence between the different elements in the road transportation network critical in understanding failure effects by identifying the important nodes in the network using the Eigen-vector centrality measure. The model is constructed from publically available data for Saint-Louis, Missouri. By performing a sensitivity analysis, we have found that the node with the highest Eigen-vector centrality measures are shown to provide a higher value within a ninety-five percent confidence level, indicating low sensitivity to changes in input parameters. This provides a measure to determine the most important nodes to place back into service to assist in restoring an urban center's supply chain in the wake of an extreme event.

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1. INTRODUCTION AND BACKGROUND

Critical infrastructure systems provide the backbone for socioeconomic vitality and security of urban areas. The US Department of Homeland Security (DHS) defines critical infrastructure systems as the assets, systems, and networks, whether physical or virtual, vital to the United States that their incapacitation or destruction would have a debilitating effect on security, national economic security, national public health or safety, or any combination thereof (DHS, 2014)." Large-scale disasters, such as earthquakes or hurricanes, have devastating impacts on the key critical infrastructure systems of a community. The likelihood that a disruption in one network will affect the functioning of other systems is very high in an interconnected infrastructure network (McEntire, 2004; Mills, 2005). The transportation system is one of the complex systems greatly affected by natural and man-made disruptions. An affected transportation system can have severe consequences on the economic vitality of a region. Hurricane Katrina made landfall in August, 2005 causing extensive flooding in New Orleans, Louisiana where over two hundred thousand homes were damaged or destroyed, and more than eight hundred thousand people were displaced. Roadways and bridges were impassable for several weeks with huge volumes of debris requiring disposal, and over two billion dollars had to be invested to restore the region's infrastructure, not including the large amount of indirect costs associated with loss of production and lost wages (Enke, Tirasirichai and Luna, 2008). Figure 1.1 depicts the damage to roadways due to Hurricane Katrina. This is just one example of the economic impact of these events, demonstrating the importance of how to best implement plans to restore transportation capabilities, making the study of transportation network at a system level essential for planning and accelerating critical infrastructure restoration.

Figure 1.1. Effect of Hurricane Katrina on the roadways of New Orleans, Louisiana. (Image from Louisiana Department of Transportation and Development

Existing decision-making techniques developed by the federal, state and local government agencies focus only on emergency responses in an event of a disruption (Veras and Jaller, 2012; Hale and Moberg, 2005; Horner and Widener, 2011). For developing a restoration scheme applicable for long-term purposes, community planners should integrate large amount of data available to make these decisions, such as location data, infrastructure data, geo-spatial data, etc. Though there are constraints in the data acquisition process, much of these data are found in the Geospatial Information Systems (GIS). GIS not only help in depicting the geographic interdependencies within critical infrastructure elements (Goodchild and Haining 2004; Greene, 2002) but also help in examining the interdependency among critical infrastructure systems (Sinton, 1992). However, one of the biggest challenges is integrating the large amount of data into a single model which facilitates multi-dimensional approach (Mitchell, 2005; Zeiler, 2010).

Graph theory analytics is used to integrate different data sets into a single model which captures the complex interdependencies of the transportation network representing true system conditions. Graph theory analytics help in modeling the different critical infrastructure elements into a graph by representing road segments as edges and intersections, bridges, and other interaction points as vertices. This allows for a quick analysis of different interfaces between the elements to be restored in the aftermath of a disaster. This in turn enables rapid assessment for decision making and hastens actions that have to be taken to restore or improve to pre-disaster living conditions, thereby revitalizing the economy, social and cultural life. The repair, restoration and replacement of the damaged facilities involve direct and indirect costs. Direct costs refer to the costs incurred due to infrastructure damages. Indirect costs refer to costs incurred due to consequences of a large-scale disaster such as freight flow interruption, temporary unemployment, etc. Damage to a particular infrastructure element can also have a cascading effect on other infrastructures. For instance, the lower capacity of the transportation network will result in lower production capacity for each industry sector due to reduced material deliveries or fewer employees having access to the company (Enke, Tirasirichai and Luna, 2008).

Thus, it is important for community planners to use the resources, labor and time efficiently to minimize the overall costs of the restoration process. This brings the need for the prioritization in the order of restoring the infrastructures as all the infrastructures need not be restored at once. This research identifies the important nodes in the network using the Eigen-vector centrality measure and helps in prioritizing the order of restoration of the infrastructures efficiently based on the importance of each node in the network in an event of a disaster.

1.1. EIGEN-VECTOR AND ITS APPLICATION USING GRAPH THEORY

A graph G can be considered as an ordered pair $G = (V, E)$ comprising of a set of vertices or nodes V together with a set of edges E where an edge is related with two vertices, and the relation is represented as an unordered pair of the vertices with respect to that particular edge (West, 2000). Graph-based methods provide a valuable tool for elucidating network structures. In this research, we focus on a particular type of graph-based method that identifies nodes which play crucial roles within the network. These nodes are characterized by a measure called "node centrality". There are many centrality measures used to analyze the graph based networks such as degree centrality, betweeness centrality, Eigen-vector centrality, etc. The degree centrality is one of the simplest centrality measures. The degree of a node is defined as:

$$x_i = \sum_j a_{ij} \tag{1}$$

Where

x_i = degree centrality of vertex i

a_{ij} = 1 if vertex i is connected to vertex j

a_{ij} = 0 if vertex i is not connected to vertex j

Degree centrality states that a node has high degree if it has strong connections to many other nodes in the graph. For directed graphs, there are two separate measures of degree centrality, such as the in-degree and the out-degree. In-degree refers to the number of edges directed to the node and out-degree refers to the number of edges that the node directs to others.

Eigen-vector centrality is a natural extension of the simple degree centrality where nodes with high connectivity are favored. The concept of Eigen-vectors and Eigen-values are usually used in the context of linear algebra or matrix theory (Anton, 1987). Eigen-vectors and Eigen-values emerged while studying the quadratic forms and differential equations. Many well-known mathematicians including Euler used the concept of Eigen-vector and Eigen-values to study the rotational motion of a rigid body and discovered the importance of the principal axes (Carter and Tapia, 2008). In linear algebra, an Eigen-vector is a non-zero vector whose direction does not change when a linear transformation is applied to it. If A is a linear transformation from a vector space V over a field F into itself and v is a vector in V that is not the zero vector, then v is an eigenvector of A if A (v) is a scalar multiple of v. This can be written as:

$$A(\vec{v}) = \lambda\vec{v} \tag{2}$$

Where λ is a scalar in the field F, known as the eigenvalue or characteristic root associated with the Eigen-vector $\vec{v}$.

For example, consider a matrix A= $\begin{bmatrix} 1 & 2 \\ 4 & 3 \end{bmatrix}$

λ is an Eigen value of A iff det(λ I_n- A) = 0

where

I_n = identity matrix.

$$\det\left(\lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 4 & 3 \end{bmatrix}\right) = 0$$

$\det\left(\begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 4 & 3 \end{bmatrix}\right) = 0$

$\det\left(\begin{bmatrix} \lambda - 1 & -2 \\ -4 & \lambda - 3 \end{bmatrix}\right) = 0$

$(\lambda - 1)(\lambda - 3) - 8 = 0$

$\lambda^2 - 3\lambda - \lambda + 3 - 8 = 0$

$\lambda^2 - 4\lambda - 5 = 0$

The above equation is referred as the characteristic polynomial.

$(\lambda - 5)(\lambda + 1) = 0$

$\lambda = 5$ or $\lambda = -1$

Assuming non-zero Eigen-vectors, $A(\vec{v}) = \lambda\vec{v}$

$\vec{0} = \lambda\vec{v} - A(\vec{v})$

$\vec{0} = \lambda I_n\vec{v} - A(\vec{v})$

$\vec{0} = (\lambda I_n - A)(\vec{v})$

For any Eigen value λ,

$E_\lambda = N(\lambda I_n - A)(\vec{v})$

Where:

E_λ = Eigen space

N = null space

When $\lambda = 5$,

$E_5 = N\left(\begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 4 & 3 \end{bmatrix}\right)$

$E_5 = N\left(\begin{bmatrix} 4 & -2 \\ -4 & 2 \end{bmatrix}\right)$

$\left(\begin{bmatrix} 4 & -2 \\ -4 & 2 \end{bmatrix}\right)\vec{v} = \vec{0}$

Null space of a matrix is equal to the null space of the reduced row echelon form of a matrix.

$\left(\begin{bmatrix} 4 & -2 \\ 0 & 0 \end{bmatrix}\right) \longrightarrow \left(\begin{bmatrix} 1 & -1/2 \\ 0 & 0 \end{bmatrix}\right) \begin{bmatrix} V1 \\ V2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

V1 – ½ V2 = 0

V1 = ½ V2

$E_5 = \left\{\begin{bmatrix} V1 \\ V2 \end{bmatrix}\right\} = t \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}$, t ε IR

$E_5 = \text{span}\left(\begin{bmatrix} 1/2 \\ 1 \end{bmatrix}\right)$

When λ = -1,

$E_{-1} = \text{N}\left(\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 4 & 3 \end{bmatrix}\right)$

$E_5 = \text{N}\left(\begin{bmatrix} -2 & -2 \\ -4 & -4 \end{bmatrix}\right)$

$\left(\begin{bmatrix} -2 & -2 \\ -4 & -4 \end{bmatrix}\right) \vec{v} = \vec{0}$

$\left(\begin{bmatrix} -2 & -2 \\ 0 & 0 \end{bmatrix}\right) \longrightarrow \left(\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}\right) \begin{bmatrix} V1 \\ V2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

V1 + V2 = 0

V1 = - V2

$E_{-1} = \left\{\begin{bmatrix} V1 \\ V2 \end{bmatrix}\right\} = t \begin{bmatrix} -1 \\ 1 \end{bmatrix}$, t ε IR

$E_{-1} = \text{span}\left(\begin{bmatrix} -1 \\ 1 \end{bmatrix}\right)$

For this example, there are two Eigen values, λ = 5 and λ = -1. This provides an infinite number of Eigen-vectors, thereby creating two Eigen spaces where each of them corresponds to one of the Eigen values.

Though Eigen-vector and Eigen-values were first used to study principal axes of the rotational motion of rigid bodies, they are now used in stability analysis, vibration analysis, atomic orbitals, facial recognition, and matrix diagonalization (Anton, 1987).

The concept of Eigenvector centrality was first introduced by Bonacich (Bonacich, 1987). Eigen-vector centrality gives each vertex or node in the network a score proportional to the sum of the scores of its neighbors. In theory, this centrality measure could be used for both directed and undirected networks. This is done by counting the number and the quality of connections at each node so that a node with few connections to some high-ranking other nodes may outrank one with a larger number of mediocre connections. Undirected networks are preferred over directed networks as a directed networks have an adjacency matrix that is asymmetric. This leads to two sets of Eigen-vectors such as the left Eigen-vectors and the right Eigen-vectors and thus, have two leading Eigen-vectors. The right Eigen-vector is usually used to define the centrality because the centrality in directed networks is bestowed by the in-degree of the vertex rather than the out-degree. In mathematical terms, a vertex that has a strongly connected component of two or more vertices or is the out-component of such a component, can have a non-zero Eigen-vector centrality measure. But, there are instances where vertices with high in-degree have high centrality even if they are not in a strongly connected component. A directed graph is strongly connected if there is a path between all pairs of vertices. Thus, the Eigen-vector centrality measure takes into account the entire pattern of the network and is suitable for transportation network analysis.

Many algorithms for computing Eigen-vector centrality measure of symmetric adjacency matrices are known. The power iteration method is one of the most efficient methods and used by the Gephi software tool (Bastian, Heymann and Jacomy, 2009). The power iteration method is an Eigen-value algorithm where for a given matrix A, the algorithm will calculate λ, which is the greatest Eigen value of A and non-zero vector v which is the corresponding Eigen-vector of λ such that it satisfies $Av = \lambda v$. The algorithm is also called as Von-Mises iteration. Google's “PageRank” algorithm is a variant of eigenvector centrality (Altman and Tennenholtz, 2005).

1.2. CAPTURING PHYSICAL INTERDEPENDENCE OF CRITICAL INFRASTRUCUTRE SYSTEMS

There are several works where the transportation network has been represented by an undirected graph with the nodes as cities and edges as traffic roads (Ip and Wang, 2011). The Critical Infrastructure Modelling System (CIMS, 2006) developed by Idaho National Laboratories (INL), uses geospatial information and performs ‘what-if’ analysis but one of the key problems with this model is that it fails to account for the interdependency between critical infrastructure systems.

In this research, the road transportation network is considered to study and develop a measure that can be used to determine restoration schemes. The road transportation network is modeled such that the intersections and state bridges are the nodes and the interstates, highways or spurs are the edges. Figure 1.2 illustrates a sample network that is modeled in such way that it captures the different modes of transportation. The restoration scheme is based on restoring the services associated with the freight flow of the transportation network. The road transportation network is considered as it greatly impacts the transport of freight across different regions. Disaster management studies fail to capture full system complexity by not combining qualitative and quantitative methodologies and the interdependencies that lead to emergent behaviors are not taken into account.

To investigate the road transportation network a graph G is constructed using real-time publically available data. These data come from the National Map (USGS, 2017), and includes items such as orthoimagery data to identify the roads and intersection under consideration.

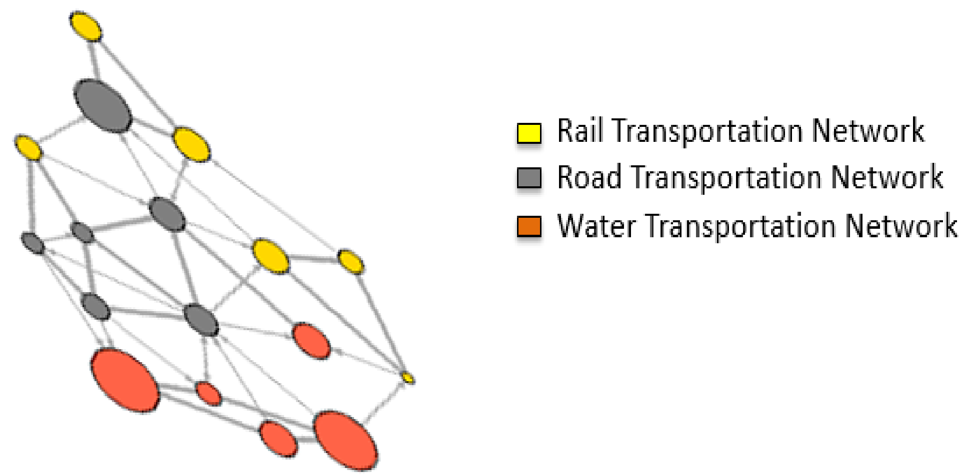

Figure 1.2. Example of a network that depicts the different modes of transportation with nodes and edges. (Image from (scipy-2011-tutorial, 2011))

This helps in identifying and representing the physical components and interactions between those different components that make up the road transportation network.

The robustness and sensitivity of different centrality measures in various networks were studied and compared when different percentages of edges and nodes in the networks were removed or added (Herald; Pastran; Zhu, 2013). The Degree centrality measure cannot be used for determining the important nodes in a transportation network as it considers only the in-degree and out-degree of a node and does not take into account the importance of its neighbors. The Betweenness centrality and the Closeness measure centrality measures are node specific and does not account for the entire network. The Katz centrality measure computes the relative influence of a node within a network by measuring the number of the immediate neighbors but connections between distant neighbors are penalized. This type of centrality measure is suitable only for applications involving directed networks such as citation networks and World Wide Web (West, 2000). On comparison with the all centrality measures, the Eigen-vector centrality measure is the most appropriate system parameter in this scenario. This is the first time that a research has been carried out to account for interdependence for a road transportation network using the Eigen-vector centrality measure. Based on the calculated centrality measure at each node, the restoration scheme which guides the decision making process is developed. The technique proposed here takes into account the system characteristics compared to existing models which lacked complexity and a robust data identification process (Veras and Jaller, 2012; Hale and Moberg, 2005; Horner and Widener, 2011; Ramachandran, et al., 2014). The area chosen for this study is Saint-Louis, Missouri. Saint Louis, MO is considered as a major hub for transportation of goods and services, consisting of road, rail, ship, and air transportation. There are four interstate highways (I-70, I-64, I-55 and I-44) that connect to a larger regional highway system, major roadways and bridges. Saint Louis has the third-largest rail hub in the nation that transports grain, gravel, crushed stone, prepared foodstuffs, fats, oils, nonmetallic mineral products, alcohol and tobacco products, etc. The major rail services across Saint Louis, MO are provided by BNSF, CSX, NS and UP. The river transportation network through the Port of Saint Louis, is 19.3 miles of riverbank on the Mississippi River that handles more than thirty two million tons of freight annually.

The Mississippi River is one of the major rivers of North America which separates the east and west of the United States. The Lambert Saint Louis International Airport is also the largest and busiest airport in the state. The large amount of freight transported through different transportation networks make Saint Louis a crucial region in terms of freight flow.

The freight flow through different transportation networks could be highly disrupted in an event of a disaster. Therefore, it is necessary to understand how the different transportation networks are interdependent and interconnected so that services could be restored in the event of a disaster. Though there are several researches being carried out (Ochab, 2012; Atsan and O¨zkasap, 2007; Herland, Pastran and Zhu, 2013), applications of Eigen-vector centrality to study the interdependence between the different components of transportation networks have seldom been done. Therefore, the goal of this research is to develop an efficient measure to be applied to a restoration scheme by capturing the interdependence between the different components of the road transportation network by taking into account the system oriented parameter of the road transportation network.

2. METHODOLOGY

Modeling critical infrastructure elements with real-world data has seldom been done as the modeling techniques are predominantly focused on developing methodologies and algorithms. A major section of research either assumed that the data are hypothetically complete and available, or synthetic data is generated for analyses when needed. This kind of approach makes it arduous to understand the complex interactions between different critical infrastructures. In this research, the interdependence between different critical infrastructure elements are illustrated by using the actual road transportation network in the Saint Louis, Missouri area as an example. The road transportation network is modelled using graph theory analytics. The road transportation network is modeled in such a way that the intersections or state bridges are the nodes and the interstates or highways are the edges. We calculate the Eigen- vector centrality measure for the road transportation network to identify the important nodes in the network. The Eigen-vector centrality principle states that the importance of each node is proportional to the importance of its neighbors. Importance refers to the connectivity of a particular node in the network. Nodes with a higher Eigen-vector centrality measure, for the overall network have a higher level of the importance in the network.

The proposed technique focusses on restoring the freight flow capacity across the road transportation network. The road transportation network is modelled as a graph (Figure2.1). using an open source python package called OSMnx. OSMnx is built using NetworkX (Aric, Daniel and Pieter, 2008) Geopandas and matplotlib (Boeing, 2017) and helps in constructing, projecting, visualizing and analyzing complex street networks. The advantage of using OSMnx python package is that one can construct street networks in one line of python code without having to acquire administrative boundary GIS data by tacking shapefiles online.

Figure 2.1. Graphical representation of Saint Louis road transportation network constructed using OSMnx.

OSMnx is also capable of constructing specific network types such as drive, walk, bike, private roads, etc. The road transportation network of Saint Louis, Missouri which is modelled as a set of nodes and edges is exported as a shapefile for further analysis using ArcMap. Figure 2.2 depicts the road transportation network of Saint Louis, MO in Arcmap software tool. The secondary and tertiary roads in Saint Louis, MO are removed using

ArcMap so as to reduce the complexity of the problem. ArcMap is an integrated application of ArcGIS software that could be used for all map-based tasks including cartography, map analysis, and editing.

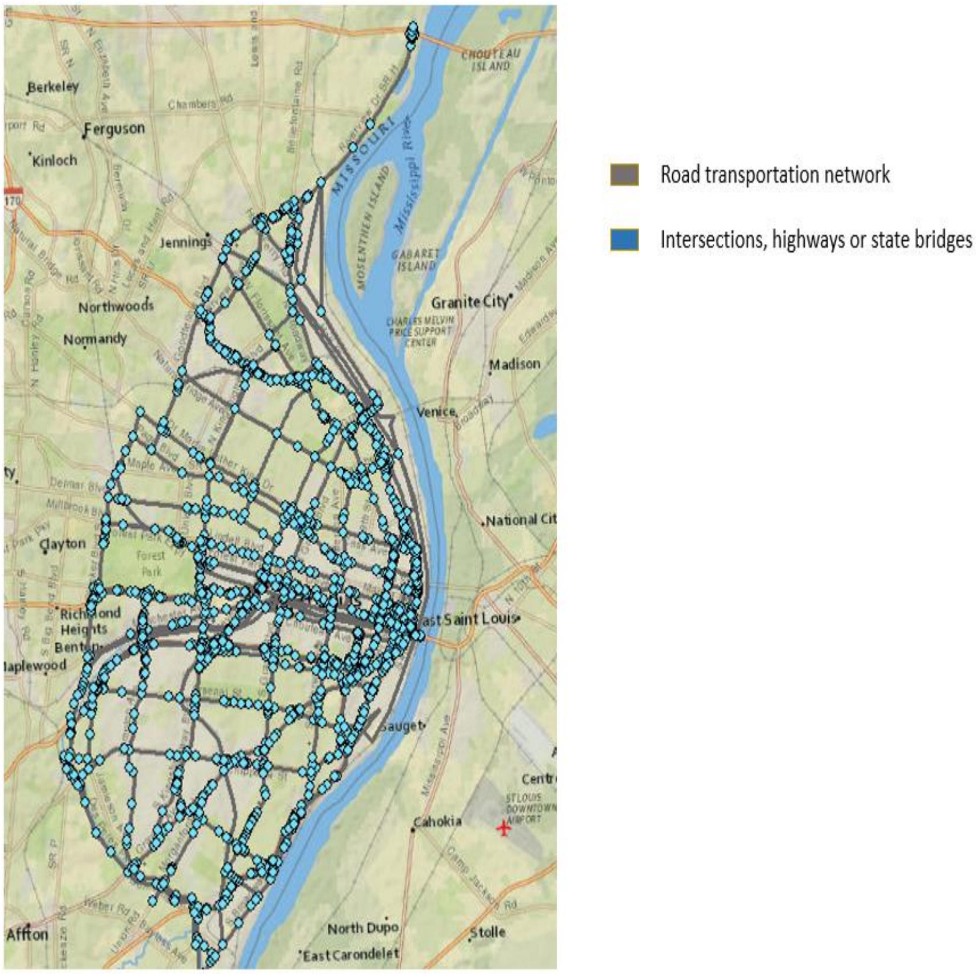

Figure 2.2. Graphical representation of Saint Louis road transportation network constructed using ArcMap.

The basic concept in creating a geometric network is to determine which feature classes will participate in the network and what role each will play. A feature is an object that stores its geographic representation as one of its properties in the row. This can be a point, line, or polygon. Points are used for point locations or for features that are too small to depict as lines or polygons. Lines are used to represent the shape and location of geographic objects, such as street centerlines, etc. Polygons are used to represent the shape and location of homogeneous feature types such as states, counties, etc. Each line and polygon can be considered as an ordered set of vertices that can be connected to form the geometric shape. Feature classes are defined as a homogeneous collections of common features, each having the same spatial representation, such as points, lines, or polygons, and a common set of attribute columns, for example, a point feature class for representing the road intersections. A geometric network is a connectivity relationship between a collection of feature classes in a feature dataset.

Using the Editor tool, new features can be created with the help of Line construction tool zooming to the area selected to add the new feature. The Edge Snapping is activated and the pointer is moved to edge to which the selection is to be snapped. The map is clicked to create new feature's vertices. Feature classes contain the geometric shape of each feature and descriptive attributes. Each feature class can be considered as a table where individual features are placed in rows and feature attributes are placed in columns. The table consists of linear features that has a unique identifier such as the Object ID, the coordinate information such as the longitude and latitude values, and a common measurement system along each linear feature such as the shape which denotes each feature's geometry. ArcGIS can record coordinates using integer numbers and handles locations with very high precision. In various ArcGIS operations, feature coordinates are handled using key geometric properties. These properties are defined during the creation of each feature class or feature dataset.

For example, the X, Y resolution indicates the precision at which X, Y coordinates within a feature class are recorded. For coordinates that are in latitude-longitude, the default X, Y resolution is 0.000000001 degrees.

The graph is modeled in such a way that this critical infrastructure element could be integrated to a larger modeling framework by considering it as a component of a larger supply interdependent critical infrastructure system. The graph depicts the connectivity to the U.S. supply chain system in the Saint Louis area and helps in understanding the geographic interdependencies across the road transportation network. The data associated with the graph such as latitude and longitude values, node ID, length, edge source and target, etc. from the attribute table are exported as a text file. This text file is then converted to a .csv (comma separated values) which is used for further analysis using a software called Gephi.

Gephi (Gephi, n.d.) is an open-source network visualization platform that is used for the visualization and analysis of the road transportation network. It iterates through visualization using dynamic filtering and is mainly used for exploratory analysis, link analysis, social network analysis and biological network analysis. Gephi supports networks up to one hundred thousand nodes and one million edges and is compatible with majority of graph file formats including CSV. Users can also visualize how a network would evolve over time by manipulating the embedded timeline. Gephi has an in-built statistics and metrics framework that is capable of calculating different network parameters such as shortest path, closeness centrality, Eigen – vector centrality , Page rank , Katz centrality and eccentricity of the network. The Eigen-vector centrality using adjacency matrix is calculated as follows:

Consider a graph G = (V, E) where V is the number of vertices and E is the number of edges. Let A be the adjacency matrix where A= $(a_{v,t})$.

$(a_{v,t})$ = 1 if vertex v is connected to vertex t

$(a_{v,t})$ = 0 if vertex v is not connected to vertex t

$$X_v = \frac{1}{\lambda} \sum_{t \in M(v)} X_t \tag{3}$$

$$X_v = \frac{1}{\lambda} \sum_{t \in M(v)} a_{v,t} x_t \tag{4}$$

Where:

M (v) is a set of the neighbors of v.

In vector notation,

$\vec{X} = \frac{1}{\lambda}$ A.$\vec{X}$

λ.$\vec{X}$ = A. $\vec{X}$

Where

A = Adjacency matrix

$\vec{X}$ = Eigen-vector of A

λ = Eigen value.

The adjacency matrix consists of 0's and 1's where 1 indicates a particular node is connected to the corresponding node and 0 indicates that that particular node is not connected to the corresponding other nodes. The process of calculating the Eigen-vector centrality measure involves solving for the Eigen values λ_i and the corresponding Eigen-vectors X_i of an n x n matrix A. The importance of the Eigen-vector centrality measure as measured above is directly related to the ability of freight to be transported across the road transportation network and helps us to understand the interfacing between the bi-modal transportation networks and develop a restoration scheme based on it.

In order to evaluate the proposed technique, data associated with the U.S air transportation system which was derived from the Bureau of Transportation Statistics (Table 2.1.) is first imported to the Gephi software tool for visualization and Eigen-vector centrality measure calculation.

Similarly, the data associated with the road transportation network such as the nodes data table (Table 2.2) and the edges data table (Table 2.3) exported from the ArcGIS software tool is imported to the Gephi software tool for the Eigen-vector centrality measure calculation.

Table 2.1. Illustration of the nodes data table of the U.S. air transportation system from the Bureau of Transportation Statistics.

FEATURID	LINKID	SOURCE	STFIPS	CTFIPS	MILES
1000001	1	D	1	125	1.22
1000002	2	D	1	125	4.24
1000003	3	D	1	125	2.41
1000004	4	D	1	125	1.26
1000005	5	D	1	125	10.88
1000006	6	D	1	125	1.19
1000007	7	D	1	125	6.55
1000008	8	D	1	125	3.59
1000009	9	D	1	125	0.97
1000010	10	D	1	125	2.41
1000011	11	D	1	125	2.26
1000012	12	D	1	125	1.62
1000013	13	D	1	125	11.48
1000014	14	D	1	125	1.33
1000015	15	D	1	73	8.57
1000016	16	U	1	73	0.69
1000017	17	D	1	73	0.43
1000018	18	D	1	73	1.56
1000019	19	D	1	73	7.77
1000020	20	U	1	73	1.17
1000021	21	D	1	73	1.99
1000022	22	U	1	73	2.04
1000023	23	D	1	73	1.05
1000024	24	U	1	73	0.71

To ensure that the node with maximum Eigen-vector centrality measure is the most important node in the graph, thirty experiments were performed where one hundred nodes are randomly selected and deleted from the network and the Eigen-vector centrality measure is recalculated. These results were used to determine a mean Eigen-vector centrality measure and a 95% confidence level.

Table 2.2. Illustration of the nodes data table.

Id	Label	lat	lon
33053203	33053203	38.63644	-90.1862
33053212	33053212	38.6772	-90.2078
33053227	33053227	38.69534	-90.2606
33053229	33053229	38.69917	-90.2619
33053674	33053674	38.66345	-90.1988
33056507	33056507	38.62304	-90.1944
33056509	33056509	38.62402	-90.1942
33056513	33056513	38.62624	-90.1933
33056652	33056652	38.62538	-90.1937
33056767	33056767	38.6243	-90.1954
33056768	33056768	38.62338	-90.1957
33056908	33056908	38.62456	-90.1904
33056909	33056909	38.62541	-90.19
33057048	33057048	38.62515	-90.1888
33057049	33057049	38.62429	-90.1892
53158234	53158234	38.56382	-90.2792
53158363	53158363	38.60622	-90.2689
53158397	53158397	38.61036	-90.304
53158429	53158429	38.61023	-90.3029
53158437	53158437	38.65219	-90.2697

Table 2.3. Illustration of the edges data table.

Source	Target	Type	Length
3056741039	3056741033	Directed	106.3138
53166394	3056741039	Directed	13.25688
3056741037	3056741039	Directed	218.0537
53159682	313032753	Directed	276.8673
313032753	312894476	Directed	724.1601
3056741048	3056741049	Directed	117.6021
3056741049	3056741050	Directed	95.28178
53166437	3056741049	Directed	196.2957
3056741053	3056741066	Directed	9.435881
3056741067	3056741053	Directed	122.8903
3056740921	3056741055	Directed	70.16377
53167930	3056741055	Directed	12.43624
3056741055	3056741054	Directed	28.83323
3056763018	53169890	Directed	67.80233

The confidence interval helps in determining how much uncertainty there is with any particular statistic with a margin of error. Confidence levels are expressed as a percentage. For a confidence interval of ninety-five percent, ninety-five percent of the time, the results will match the results you get from a population when you repeat an experiment over and over again and helps to validate our results. The number of samples required depend on the analysis to be done and the properties such as mean, median, variance, etc. of the sample being studied. The number of samples used in this research is thirty because beyond thirty samples, the sample size is not considered small ((Khan, n.d.). Also, when the number of samples taken are thirty, it is reasonable to assume that if the number of samples is thirty or more, the mean has normal distribution with the sample variance being equal to the population variance divided by the sample size i.e. (σ^2 / n).

Where:

σ = Variance

n = Sample size

The confidence interval is calculated using the T-distribution. The T-distribution is used when the behavior of the population is not known and when the samples are not very large. The first step in calculating the confidence interval involves calculating the α value. The α value is calculated by

α = 100% - percentage of confidence level

In this case, confidence level= 95%

α = 100% - 95%

α = 5% = 0.05

The α value is divided by two to find the α value for one half of the T-distribution

α =0.05/2 = 0.025

The degrees of freedom is calculated by subtracting the sample size by 1

Degrees of freedom = 30 -1 = 29

Using the T-distribution table, the T-value corresponding to the computed α value and degrees of freedom is found to be 2.045.

The next step involves calculating the standard error. Standard error is calculated by dividing the standard deviation by the square root of n where n is the number of samples. The confidence interval is determined by adding or subtracting a value calculated by multiplying T-value and standard error from the mean.

In order to develop a restoration scheme that focuses on restoring ninety-five percent of the freight flow capacity across the road transportation network, the order of restoring the connectivity between nodes and edges are prioritized based on the Eigen-vector centrality measure. Ninety-five percent restoration is considered so as to ensure that there is maximum freight flow across the road transportation network, thereby minimizing the indirect costs. A restoration decision tree is then developed to carry out the restoration process. The restoration tree can be used to help community planners to evaluate the road transportation network based on the amount of destruction and also help in determining if a particular transportation mode could be substituted for another mode in order to maintain continuous freight flow. Efficient restoration schemes can be developed based on the restoration decision tree and system specific information such as the freight and infrastructure data.

3. RESULTS

This results section is divided into two sub-sections. The first sub-section presents the results associated with evaluating the air transportation system of the U.S and the second sub-section describes the results associated with the road transportation network.

3.1. VISUALIZING TRANSPORTATION SYSTEMS

The U.S air transportation system consists of three hundred and thirty one nodes and one thousand three hundred and sixty four edges where each node refers to an airport and the edge refers to the flight route between airports. The Eigen-vector centrality measure is then calculated for each node in the network. Table 3.1 depicts the calculated Eigen-vector centrality measures for the air transportation network in the U.S.

Table 3.1. Illustration of few nodes and associated Eigen centrality measure of the Air Transportation Network in the U.S.

id	label	Eigen-vector centrality
331	Pago Pago Intl	0.021906675
330	Babelthuap/Koror	8.40E-04
329	Guam Intll	0.006906634
328	Rota Intl	8.40E-04
332	West Tinian	3.57E-04
327	Saipan Intl	0.001375303
326	Johnston Atoll	0.005933433
120	Cedar Rapids Mun	0.104250017
119	Bradley Intl	0.44927527
118	Chicago O'hare Int	1
117	Erie Intl	0.020245685
116	Klamath Falls Intll	0.01402894
115	Elmira/Corning Re	0.021002725
114	Greater Rockford	0.024767695
113	Binghamton Regio	0.035984283
112	Detroit Metropolit	0.782506181
5	Nome	0.004454191
4	Fairbanks Intl	0.019064624
3	Ralph Wien Memo	0.004454191
2	Deadhorse	0.00528161
1	Wiley Post-Will Ro	0.00528161

The node with ID 118 which is the Chicago O'hare Airport is found to have the maximum Eigen-vector centrality measure in the network. All the other nodes will be arranged in the descending order of their Eigen-vector centrality measures to prioritize which infrastructure element should be restored first. The node with ID 25 which is the Gustavus Airport in Alaska is found to have the lowest Eigen vector centrality measure.

Figure 3.1 depicts the network visualization of the Air Transportation Network in the U.S using Gephi software tool. The nodes are not geographically located in this network visualization.

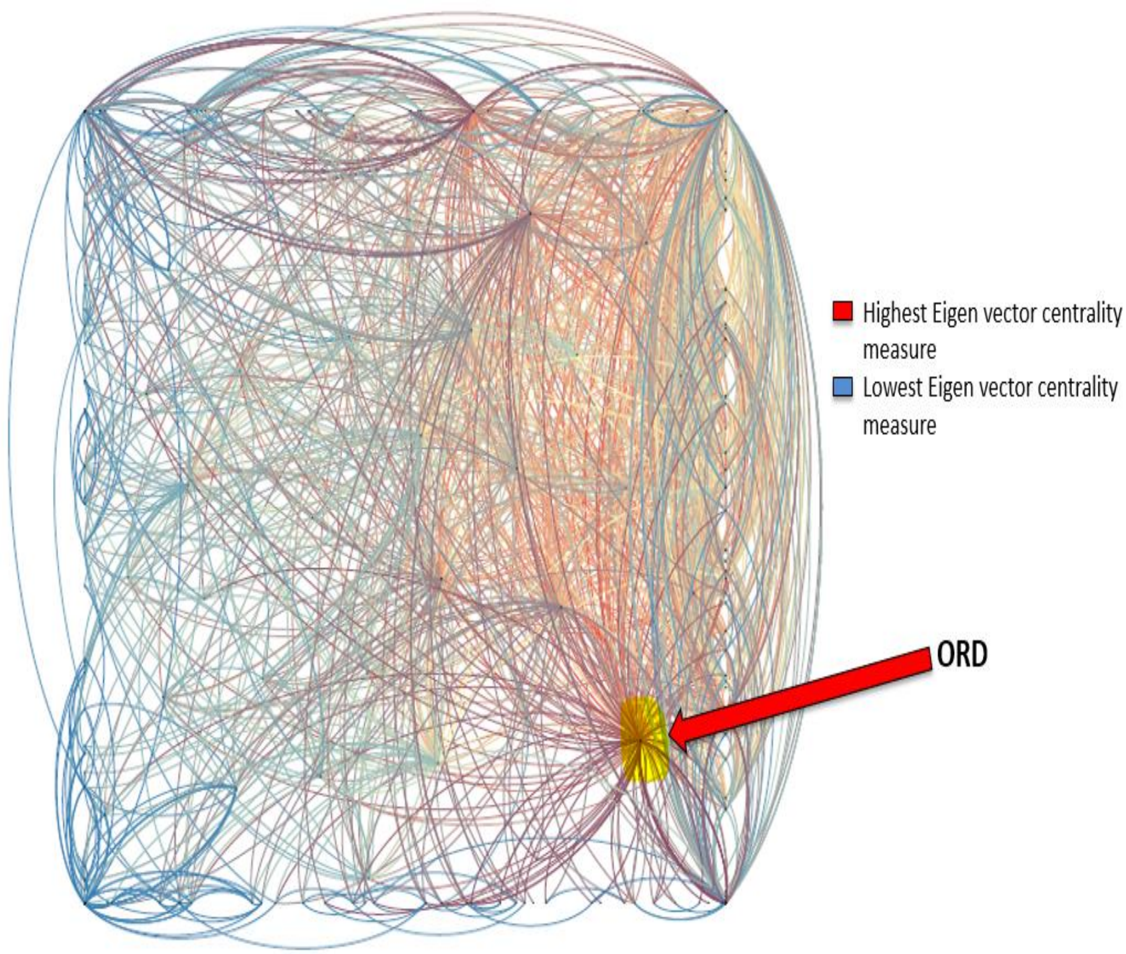

Figure 3.1. Illustration of the node that has the highest Eigen-vector centrality measure.

The Gephi software tool separates the nodes with low Eigen-vector centrality measure from the nodes with high Eigen-vector centrality measure by placing the nodes with low Eigen-vector centrality measure to the far left end of the network and pushing the nodes with high Eigen-vector centrality measure to the far right end of the network. The edges connecting the nodes with low Eigen-vector centrality measure are indicated with blue whereas edges connecting the nodes with high Eigen-vector centrality measure are indicated with red.

3.2. EVALUATING THE ROAD TRANSPORTATION NETWORK USING GEPHI

The road transportation network consists of one thousand two hundred and fifty eight nodes, and two thousand one hundred and seventeen edges.

Table 3.2. Illustration of few nodes of the graph and their associated Eigen-vector centrality measure.

ID	Label	lat	lon	Eigen-vector Centrality
53166827	53166827	38.63644	-90.1862	0.273274882
3.19E+08	3.19E+08	38.6772	-90.2078	0.054093928
53166858	53166858	38.69534	-90.2606	0.273315821
5.42E+08	5.42E+08	38.69917	-90.2619	0.231029638
53166925	53166925	38.63112	90.21554	1
53166926	53166926	38.63644	-90.1862	0.314366693
53166928	53166928	38.6772	-90.2078	0.287862453
53166929	53166929	38.69534	-90.2606	0.287814377
53166930	53166930	38.69917	-90.2619	0.392818743
53166932	53166932	38.66345	-90.1988	0.581970635
53166933	53166933	38.62304	-90.1944	0.98016743
53166936	53166936	38.62402	-90.1942	0.284920888
53166945	53166945	38.62624	-90.1933	0.27333588
53166950	53166950	38.62538	-90.1937	0.273317115
53166953	53166953	38.6243	-90.1954	0.27331715
53167006	53167006	38.62338	-90.1957	0.27331693
53168967	53168967	38.62456	-90.1904	0.273317113
53167029	53167029	38.62541	-90.19	0.21604111
53168969	53168969	38.62515	-90.1888	0.273317111
53167034	53167034	38.62429	-90.1892	0.285266247
53167108	53167108	38.56382	-90.2792	0.273318271

The node with node ID 53166925 is found to have the maximum Eigen-vector centrality measure in the network (Figure 3.2). All the other nodes will be arranged in the descending order of their Eigen-vector centrality measures to prioritize which infrastructure element should be restored first.

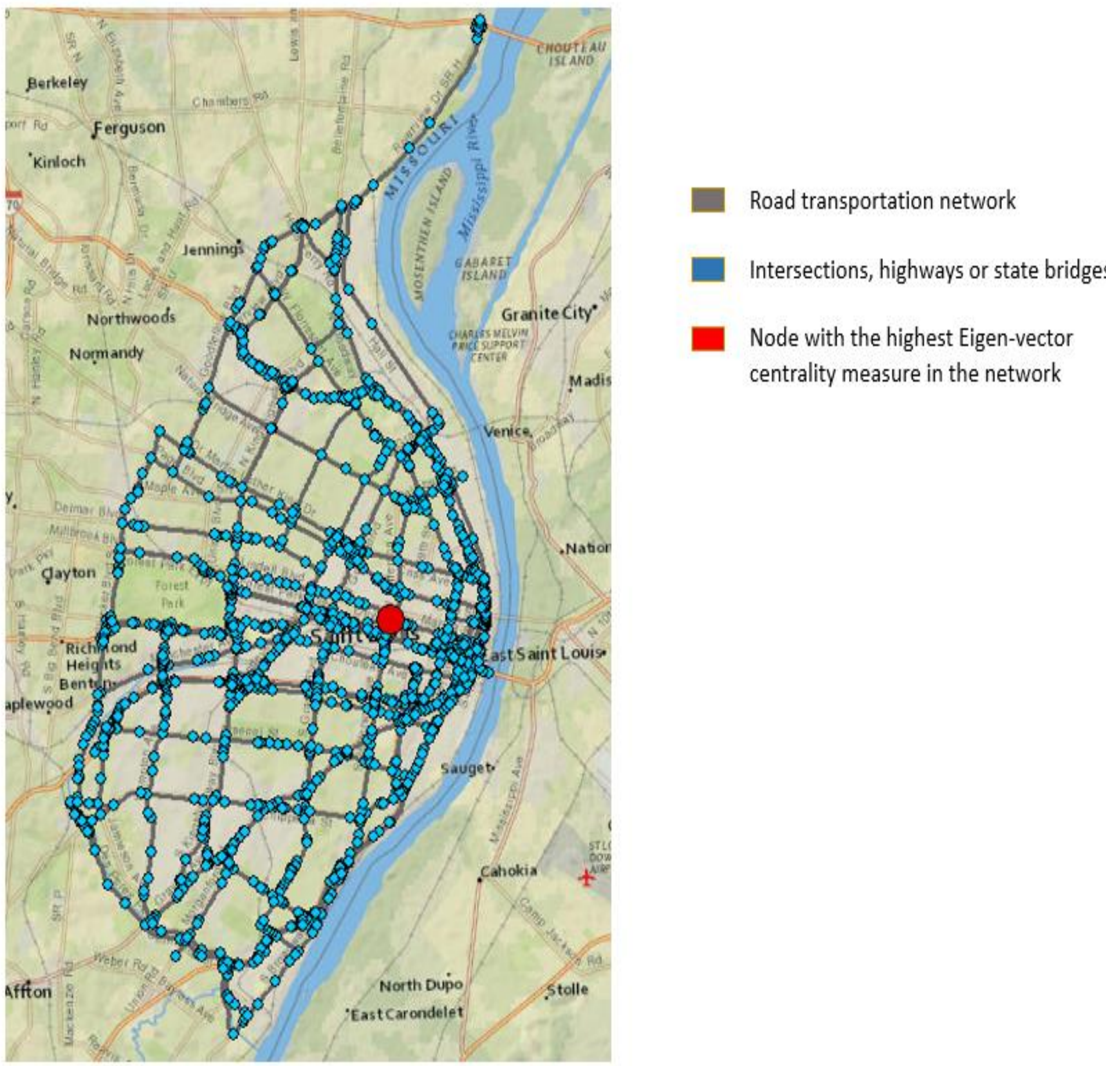

Figure 3.2. Illustration of the node with the highest Eigen-vector centrality measure in the network using Arcmap.

The node is located based on the node ID, longitude and latitude values. This node is the most critical node in the network based on the importance defined by the Eigen-vector centrality measure. This node which corresponds to the intersection between North Jefferson Avenue, South Jefferson Avenue, Market Street and I-64 in the city of Saint Louis, has high Eigen-vector centrality measure due to its connectivity and the network will be most impacted if this particular node is disrupted in an event of a disaster. Also, there are other nodes in the network with Eigen-vector centrality measures not equal to 1. These nodes are also important and play a key role while developing restoration schemes. The restoration schemes are developed by prioritizing the order of restoration of all the infrastructure elements and this prioritization is done based on the descending order of the centrality measure at each node.

Figure 3.3 depicts the network visualization of the road transportation network using Gephi software tool. The nodes with low Eigen-vector centrality measure are indicated with blue and the nodes with high Eigen-vector centrality measure are indicated with red. Though the nodes in the visualization are not geographically located, community planner can easily identify the key nodes in the network. The Eigen-vector centrality measure at each node in the network may or may not change when a node is connected or removed. The Eigen-vector centrality measure at each node in the network is dynamic and the centrality measure might change depending on how a node is connected or removed from the network.

When the node with the highest Eigen-vector centrality measure is removed from the network, the Eigen-vector centrality measure of the nodes connected to the node with highest Eigen-vector centrality measure tend to decrease. Also, another node in the network will have the highest Eigen-vector centrality measure when the node with the highest Eigen-vector centrality measure is removed (Figure 3.4). This was evident during the sensitivity analysis when hundred nodes were randomly selected and deleted from the network.

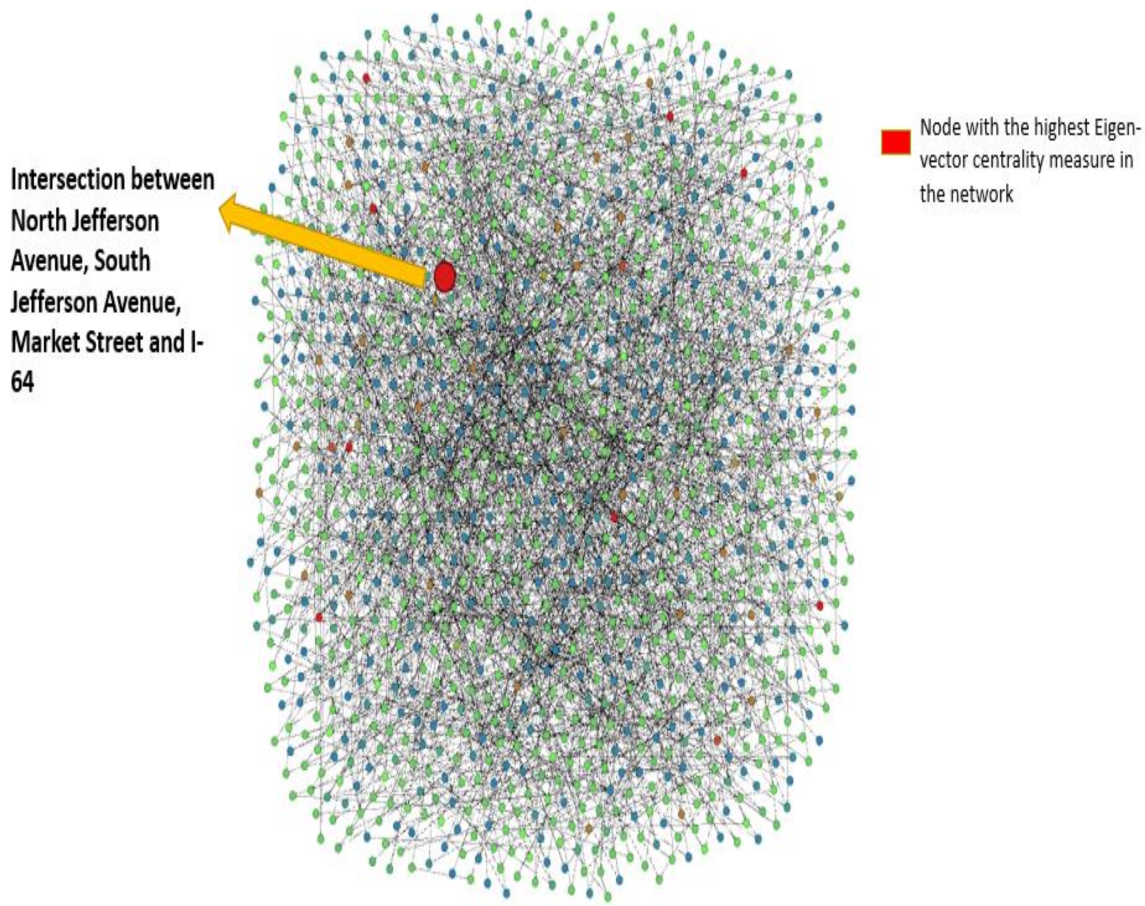

Figure 3.3. Road transportation network visualization using Gephi software tool.

The average value of the Eigen-vector centrality measures was calculated for thirty experiments where one hundred nodes were randomly removed from the network (Table

3.3.). The mean, standard deviation, standard error and the confidence interval are calculated for each of the nodes in the network.

Table 3.3 shows that the node with node ID 53166925 continues to have a high Eigen-vector centrality measure with a confidence interval 0.98 to 1 at a ninety-five percent confidence level. This shows that the node with the highest Eigen-vector centrality measure continues to have a higher value irrespective of certain nodes being deleted from the network.

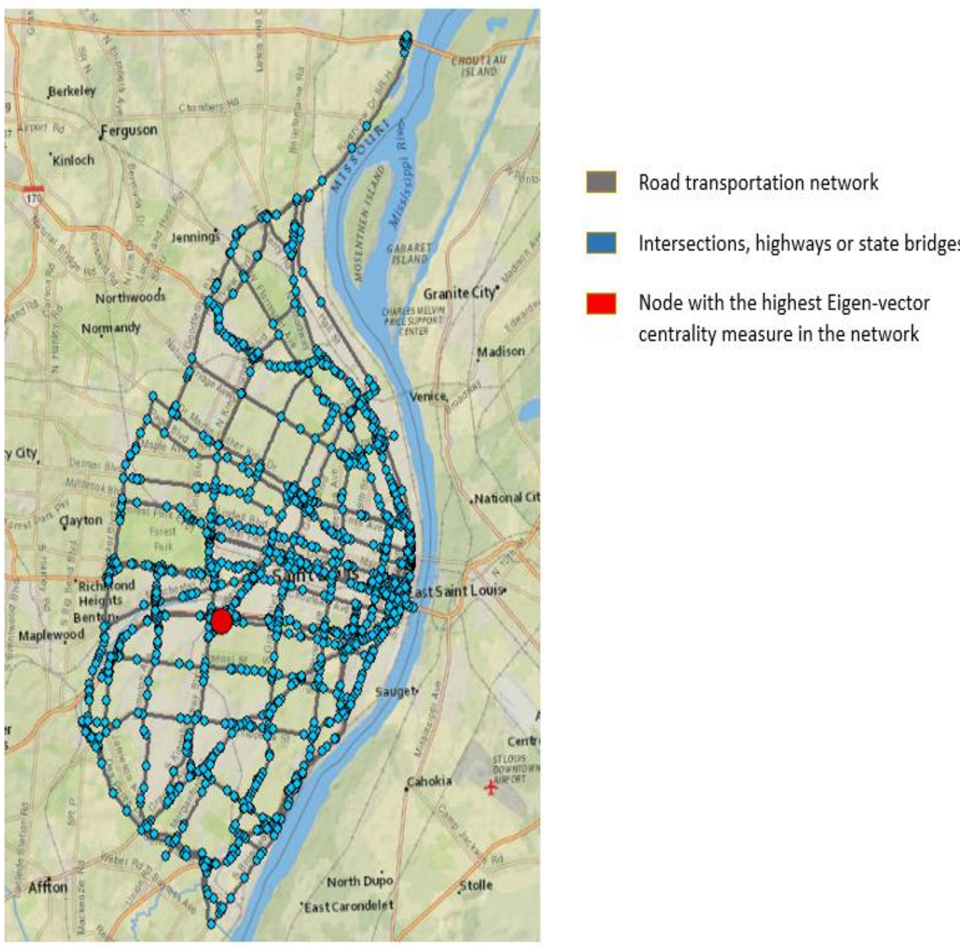

Figure 3.4. Illustration of the change in node with the highest Eigen-vector centrality measure in the network using Arcmap.

The nodes are arranged in the descending order of the upper limit of their confidence interval. This shows the order of importance of each node in the network and helps to prioritize the order of restoration of infrastructure elements in an event of a disaster.

Table 3.3. Illustration of few nodes from the graph arranged in the descending order of their upper limit of the confidence interval.

S.NO	ID	Mean	Std. Deviation	std error	Confidence Interval	
					Lower Limit	Upper limit
1	53166925	0.987941	0.034932355	0.00638	0.97489853	1.000983515
2	53161880	0.975441	0.047753557	0.00872	0.95761155	0.993270493
3	53166256	0.968298	0.057507484	0.0105	0.94682693	0.989769403
4	53171675	0.954012	0.071094341	0.01298	0.92746837	0.980556535
5	53169191	0.94687	0.071138637	0.01299	0.92030897	0.973430216
6	53162296	0.939727	0.075360804	0.01376	0.91158971	0.967863766
7	53163245	0.93437	0.076212455	0.01391	0.90591459	0.962824599
8	53168781	0.930798	0.075391893	0.01376	0.90264953	0.958946801
9	53167723	0.923655	0.073202494	0.01336	0.89632412	0.950986501
10	53165912	0.914727	0.071248172	0.01301	0.88812522	0.941328256

To validate the results obtained using the proposed technique, the important nodes identified in the network based on the Eigen-vector centrality measure are compared to the actual traffic flow counts at those intersections as provided by the Missouri Department of Transportation (MoDOT, 2015). Table 3.4 shows the average annual traffic flow count across the nodes that have high Eigen-vector centrality measures.

The average annual traffic flow count at each node (intersection) is calculated by taking the average of the sum of the average annual traffic count across the associated edges (roads). The average traffic flow count helps to understand the amount of commuter traffic and freight transported at a particular node and the road capacity being utilized.

High average annual traffic flow count at a particular node indicates that the freight transported across that node is high. The Eigen-vector centrality measure accounts for the connectivity of a particular node in the network, and with higher connectivity, it would follow that there would be higher traffic flow at a particular node. Therefore, connectivity of a node can be correlated with the amount of traffic across the edges associated with that node.

Table 3.4. Illustration of nodes with high Eigen-vector centrality measure and their associated traffic flow counts.

Eigen- Vector Centrality Measure	Name	Average annual Traffic Counts	Major Interstate/ Highways connection	Average Annual Traffic Count across the nodes identified based on Eigen-vector centality measure
1	North Jefferson Avenue and Market Street	79020	I-64	84395.16667
	South Jefferson Avenue and Market Street	76837.5	Chouteau Avenue	
	I-64	97328	I-44	
0.98025	Salsbury Street	27975	I-70	27975
	East Natural Bridge Avenue			
	Parnell Street			
0.980167	Page Boulevard	4324	I-64	26864.25
	Dr. Martin Luther King Drive	3054		
	North Grand Boulevard	2751		
	I-64	97328		
0.980166	South Kingshighway Boulevard	14678, 14784, 16747	I-44	15403
	Chippewa Street			
0.980165	Chippewa Street	14784	I-44	14731
	Hampton Avenue	14678		

Table 3.4 gives a comparison of the traffic flow count for the roads at several intersections with the highest Eigen-vector centrality measure. The node with the highest Eigen-vector centrality measure also had the highest average annual traffic count. As the Eigen-vector centrality measure decreases, so does the average annual traffic counts for those intersections.

The identified nodes are also connected to major interstates such as the I-64, I-44 and I-70 across Saint Louis. MO and according to the 2011 MoDOT freight plan (MoDOT, 2011), the truck density by tons is around forty-eight million tons of freight across the interstates I-70, I-64 and I-44. This accounts for the high average annual traffic flow count across the identified nodes. Therefore, the important nodes identified based on the Eigen-vector centrality measure are actually important in the network in terms of freight flow.

4. CONCLUSION

This work demonstrates the use of an Eigen-vector centrality measure to determine the importance of a critical infrastructure element to the overall critical infrastructure system. This was demonstrated on a road transportation system, but it can be extrapolated to include multiple types of infrastructure systems. This measure can be used to determine infrastructure connectivity to help develop a restoration framework which in turn aids in the post-disaster restoration efforts to allow efficient reconnection of an urban environment to the larger economic infrastructure. Restricted access to infrastructure data poses a major challenge for developing restoration schemes. However, this research presents a methodology for identifying and analyzing road transportation networks by constructing models that can utilize real-time, publically available data to create representative models. For modeling the road transportation network, GIS is used to represent real-world features which are then analyzed using graph theory analytics representing transportation elements as vertices and edges.

The sensitivity analysis performed to identify the most important nodes in the network based on the Eigen-vector centrality measure show the resiliency of the approach. From Table 3.3, it is evident that the node with the highest Eigen-vector centrality measure continues to have a higher value regardless of nodes being deleted from the network. The lower limit of the most important node is 0.97 and the upper limit is taken as 1 because it is the maximum Eigen-vector centrality measure a node can have. The confidence interval helps to account for the uncertainty associated with the Eigen-vector centrality measure for each of the nodes when the network is disrupted. This statistical analysis shows that the use of a network based Eigen-vector centrality measure provides consistent results as to the importance of high traffic nodes in the transportation system, lending credibility to the proposed methodology. Comparing the actual traffic flow counts and the amount of freight transported across the imported nodes identified based on the Eigen-vector centrality measure validates the findings of this research.

This technique maps the physical interactions between the different components of the road network such as roads, intersections and bridges by identifying the important nodes based on the Eigen-vector centrality measure to allow for prioritizing node restoration in the order of their importance to develop a system level restoration plan. This restores the flow of goods and services in the aftermath of a disruption, thereby achieving the research objective of developing efficient restoration schemes for a road transportation network. While previous research works failed to provide an optimal solution to model and map the interdependencies between critical infrastructure elements, the validation results indicate that integrating different critical infrastructure elements into a single model using geospatial data can help in developing efficient disaster restoration frameworks. This approach is direct and the results are promising, potentially playing a crucial part in restoration efforts. The results also demonstrate that sufficient data can be derived from publically available data sets. This research stresses the importance of using real-world data to model critical infrastructure systems. In addition, the need to understand transportation networks at a system level by taking into account the interactions between the different elements of the transportation network improves the restoration schemes. One of the major advantages of this methodology is its scalability such that the model could be used for different regions and different infrastructure elements if sufficient data are available.

The ability to visualize the connectivity of the network and identify the high Eigenvector centrality measure nodes is also beneficial to community planners. It provides a connectivity representation separate from physical location that provides a perspective on how an infrastructure element impacts the other parts of the transportation network. It also provides a visual check on the impact of removing elements from the overall infrastructure.

5. FUTURE WORK

Future work will include extending this research technique to other critical infrastructure elements. The interdependent nature of critical infrastructures or use of real-world data were seldom done in most of the modeling techniques. Modeling real-world scenarios involves mapping and understanding geographic interdependencies among different critical infrastructure elements. Other parameters such as restoring costs and freight flow at each node could be added to the existing technique as weights in the network to create a better understanding of the system. Most of the databases related to the critical infrastructure elements are proprietary and cannot be easily accessed. This calls for a detailed analysis to determine which data are required for modeling the supply chain network. This research will provide an in-depth understanding on the critical infrastructures and its restoration in an event of a natural or man-made disaster.

APPENDIX

Data Table for the Eigen-vector centrality measure at each node:

S.NO	Node ID	Eigen-vector centrality measure
1	53159050	0.147779446
2	53159103	0.177695207
3	53159108	0.098658022
4	53159134	0.025117343
5	1307387128	0.181350623
6	53159204	0.057043966
7	53159285	0.025116237
8	53159298	0.025116237
9	53159304	0.099882379
10	53159365	0.273306976
11	53159376	0.271826639
12	53159395	0.025116237
13	53159398	0.188669364
14	53159400	0.101149749
15	53159402	0.057483356
16	2925078044	0.268670352
17	53159560	0.179185348
18	53159577	0.10413764
19	53159604	0.268442958
20	53168916	0.40444738
21	53159612	0.257581804
22	1830987470	0.197521162
23	53159631	0.098972994
24	53159682	0.273561572
25	53159779	0.435763375
26	53159791	0.273253427
27	53159797	0.031913141
28	53159823	0.26749117
29	53159875	0.070583226
30	53159892	0.088338965
31	53159912	0.313440441
32	1975527444	0.273317111
33	53159962	0.273315677
34	4220528684	0.273319809
35	4220528686	0.025116237

36	53159995	0.10413764
37	53160010	0.307585945
38	53160024	0.273317111
39	53160036	0.273034866
40	53160044	0.283963946
41	53160073	0.206363227
42	53160145	0.025116256
43	53160147	0.047676845
44	53160159	0.228792621
45	53160209	0.026265098
46	53160211	0.032226432
47	53160221	0.145054624
48	53160245	0.314059926
49	53160267	0.27330967
50	53160298	0.273254884
51	53160320	0.273263564
52	528165269	0.273373314
53	53160342	0.254155344
54	53160368	0.025338739
55	53160401	0.273317111
56	53160423	0.179184225
57	53160436	0.273036019
58	53160493	0.271776874
59	3056740920	0.025116237
60	3056740921	0.025116237
61	3056740926	0.025117343
62	53160542	0.053019503
63	53160574	0.581951816
64	53160599	0.097542402
65	53160604	0.056738623
66	53160609	0.04991153
67	3056741033	0.035990296
68	3056741037	0.085933994
69	3056741041	0.028657013
70	3056741043	0.025338422
71	3056741044	0.025159965
72	3056741045	0.025123678
73	3056741048	0.025116382
74	3056741050	0.025116238
75	3056741054	0.025116237
76	53160641	0.27331715

77	3056741064	0.025116237
78	3056741066	0.025116237
79	53160655	0.313440441
80	53160662	0.170066253
81	53160680	0.581971317
82	53160879	0.273616619
83	1624353858	0.273317111
84	53161096	0.392703385
85	53161119	0.276201233
86	53161123	0.274050784
87	53161154	0.257581804
88	53161157	0.268442953
89	53161159	0.272047783
90	53161162	0.273288492
91	53161165	0.273195441
92	1848847567	0.112481989
93	53161174	0.270406878
94	53161176	0.262049053
95	53161179	0.23679496
96	53161187	0.152641688
97	53161196	0.025116237
98	1374756054	0.044055949
99	53161226	0.273317092
100	1828138261	0.091186541

Data table that illustrates the confidence interval calculation:

S.NO	ID	Mean	Std. Deviation	std error	Tvalue*SE	95% Confidence Interval	
						Lower Limit	Upper limit
1	3056741039	0.361214901	0.071976415	0.013141035	0.026873417	0.334341484	0.388088318
2	3056741033	0.325463098	0.05735448	0.010471447	0.02141411	0.304048988	0.346877208
3	53166394	0.093578722	0.020802358	0.003797974	0.007766856	0.085811866	0.101345578
4	3056741037	0.27356563	0.060844485	0.011108632	0.022717153	0.250848476	0.296282783
5	53159682	0.012695064	0.002462859	0.000449655	0.000919543	0.01177552	0.013614607
6	313032753	0.042785454	0.007119315	0.001299803	0.002658097	0.040127357	0.045443551
7	312894476	0.337974749	0.092365938	0.016863636	0.034486136	0.303488613	0.372460885
8	3056741048	0.216322886	0.065054682	0.011877306	0.02428909	0.192033796	0.240611975
9	3056741049	0.289758386	0.04939679	0.009018579	0.018442993	0.271315393	0.30820138
10	3056741050	0.259380973	0.034240499	0.006251431	0.012784177	0.246596796	0.27216515
11	53166437	0.096217026	0.019004449	0.003469722	0.007095581	0.089121445	0.103312607
12	3056741053	0.135789411	0.005756335	0.001050958	0.00214921	0.133640201	0.13793862
13	3056741066	0.115124759	0.003585235	0.000654571	0.001338599	0.113786161	0.116463358
14	3056741067	0.17086235	0.011151729	0.002036018	0.004163657	0.166698693	0.175026007
15	3056740921	0.105445506	0.0029334	0.000535563	0.001095226	0.10435028	0.106540733
16	3056741055	0.194160824	0.020736714	0.003785989	0.007742347	0.186418477	0.201903171
17	53167930	0.090616217	0.023322636	0.004258111	0.008707838	0.081908379	0.099324054
18	3056741054	0.279381252	0.038732624	0.007071577	0.014461375	0.264919876	0.293842627
19	3056763018	0.166230313	0.006602505	0.001205447	0.002465139	0.163765174	0.168695452
20	53169890	0.31129082	0.013962729	0.002549234	0.005213183	0.306077636	0.316504003
21	1639568941	0.218045238	0.010923616	0.00199437	0.004078487	0.213966751	0.222123726
22	3056763087	0.241661686	0.021870235	0.00399294	0.008165563	0.233496123	0.249827249
23	3056763034	0.282035161	0.009879378	0.001803719	0.003688606	0.278346555	0.285723767
24	3056763040	0.468345378	0.017267651	0.003152627	0.006447123	0.461898255	0.474792501
25	3056763094	0.006579882	5.92287E-05	1.08136E-05	2.21139E-05	0.006557768	0.006601996
26	3056763053	0.370207296	0.012547864	0.002290916	0.004684923	0.365522372	0.374892219
27	53171558	0.286249576	0.018362541	0.003352526	0.006855916	0.279393661	0.293105492
28	53158560	0.110419037	0.050054277	0.009138619	0.018688476	0.091730562	0.129107513
29	3056763044	0.379414816	0.03953277	0.007217663	0.014760121	0.364654694	0.394174937
30	313305400	0.310465693	0.027250068	0.004975159	0.0101742	0.300291493	0.320639893
31	3056763054	0.369624516	0.028971851	0.005289512	0.010817052	0.358807464	0.380441568
32	546688591	0.097813692	0.035902097	0.006554796	0.013404558	0.084409134	0.11121825
33	3056740920	0.257756525	0.030214287	0.005516349	0.011280933	0.246475592	0.269037458
34	3056741065	0.21707201	0.021179476	0.003866826	0.007907658	0.209164352	0.224979668
35	4284538997	0.171546561	0.0131333	0.002397802	0.004903504	0.166643057	0.176450066
36	3056740925	0.216316962	0.020841703	0.003805157	0.007781546	0.208535416	0.224098508
37	53169901	0.127428002	0.025329251	0.004624467	0.009457036	0.117970966	0.136885038
38	53170823	0.194331716	0.041967694	0.007662218	0.015669235	0.178662481	0.210000951
39	1828192564	0.095574818	0.009632076	0.001758569	0.003596273	0.091978545	0.099171091

40	1828192573	0.095902749	0.005627296	0.001027399	0.002101031	0.093801718	0.09800378
41	1828192583	0.096249147	0.014584155	0.00266269	0.005445201	0.090803946	0.101694348
42	1828192577	0.11091452	0.022380572	0.004086115	0.008356105	0.102558415	0.119270625
43	1828192565	0.100156797	0.018941072	0.003458151	0.007071919	0.093084879	0.107228716
44	53171459	0.345585694	0.077770337	0.014198856	0.02903666	0.316549034	0.374622355
45	1828192566	0.262473386	0.052403534	0.009567533	0.019565604	0.242907782	0.28203899
46	1828192581	0.200078356	0.033799875	0.006170985	0.012619664	0.187458692	0.21269802
47	1828192568	0.173059941	0.03554504	0.006489607	0.013271246	0.159788696	0.186331187
48	1828192571	0.238315056	0.050860937	0.009285894	0.018989653	0.219325403	0.25730471
49	3080286086	0.218163267	0.020024988	0.003656046	0.007476614	0.210686653	0.225639881
50	53171507	0.28566772	0.010382806	0.001895632	0.003876568	0.281791152	0.289544289
51	1828192569	0.352355412	0.012044986	0.002199103	0.004497167	0.347858245	0.356852578
52	3079590591	0.100098239	0.002600226	0.000474734	0.000970831	0.099127408	0.101069071
53	1828192575	0.320018108	0.011201753	0.002045151	0.004182334	0.315835774	0.324200441
54	1828192570	0.100130176	0.002603227	0.000475282	0.000971952	0.099158224	0.101102128
55	1828192580	0.100104189	0.002600844	0.000474847	0.000971062	0.099133126	0.101075251
56	53171531	0.092170132	0.025288453	0.004617019	0.009441803	0.082728329	0.101611935
57	1830987470	0.234737886	0.019693575	0.003595538	0.007352876	0.22738501	0.242090762
58	1828192572	0.209607959	0.012689595	0.002316792	0.004737841	0.204870119	0.2143458
59	1828192585	0.174794551	0.007818889	0.001427527	0.002919293	0.171875257	0.177713844
60	53168344	0.093246975	0.025080904	0.004579126	0.009364312	0.083882663	0.102611287
61	1828192576	0.254194788	0.02975996	0.0054334	0.011111304	0.243083484	0.265306092
62	1828192579	0.141639118	0.005051852	0.000922338	0.001886181	0.139752937	0.143525298
63	1828192582	0.100099216	0.002600338	0.000474755	0.000970873	0.099128343	0.101070089
64	3079590592	0.100098369	0.002600242	0.000474737	0.000970837	0.099127532	0.101069206
65	3581542743	0.006579872	5.81763E-05	1.06215E-05	2.1721E-05	0.006558151	0.006601593
66	620362088	0.26670206	0.088788788	0.016210541	0.033150556	0.233551504	0.299852615
67	620364172	0.182515456	0.052858605	0.009650617	0.019735511	0.162779944	0.202250967
68	53159779	0.141441293	0.029417177	0.005370817	0.010983321	0.130457971	0.152424614
69	564272949	0.135336232	0.029350975	0.00535873	0.010958603	0.124377628	0.146294835
70	620364179	0.193912484	0.019506506	0.003561385	0.007283031	0.186629453	0.201195516
71	564272925	0.04255551	0.008185712	0.0014945	0.003056252	0.039499258	0.045611761
72	620364195	0.037179245	0.004887753	0.000892378	0.001824912	0.035354333	0.039004157
73	1640174339	0.006122205	0.001661621	0.000303369	0.00062039	0.005501816	0.006742595
74	53166152	0.006579872	5.81763E-05	1.06215E-05	2.1721E-05	0.006558151	0.006601593
75	53162418	0.03169522	0.00129679	0.00023676	0.000484175	0.031211045	0.032179395
76	53166158	0.013159744	0.000116353	2.1243E-05	4.34419E-05	0.013116302	0.013203186
77	3633611433	0.006579872	5.81763E-05	1.06215E-05	2.1721E-05	0.006558151	0.006601593
78	534479592	0.038509813	0.000440674	8.04557E-05	0.000164532	0.038345281	0.038674345
79	53174748	0.006579872	5.81763E-05	1.06215E-05	2.1721E-05	0.006558151	0.006601593
80	3056741041	0.346493333	0.076146134	0.013902318	0.028430241	0.318063092	0.374923574
81	2465891065	0.276861162	0.053043174	0.009684314	0.019804423	0.257056739	0.296665584
82	3056741043	0.213066137	0.033496139	0.00611553	0.01250626	0.200559877	0.225572397
83	312083238	0.282830472	0.073893897	0.013491118	0.027589336	0.255241136	0.310419809
84	312083240	0.222155893	0.050345201	0.009191734	0.018797096	0.203358797	0.24095299

85	33053203	0.349093171	0.100914235	0.018424334	0.037677764	0.311415407	0.386770934
86	312084076	0.551454752	0.057054282	0.010416639	0.021302027	0.530152725	0.572756779
87	53176434	0.354376946	0.066924721	0.012218726	0.024987295	0.329389651	0.379364241
88	1780578622	0.653241767	0.115346207	0.02105924	0.043066145	0.610175622	0.696307913
89	53171550	0.006123658	0.001661997	0.000303438	0.00062053	0.005503128	0.006744189
90	53166221	0.030604137	0.004876337	0.000890293	0.00182065	0.028783487	0.032424787
91	33056909	0.236536395	0.036104373	0.006591726	0.013480081	0.223056314	0.250016475
92	33057048	0.364430409	0.040684792	0.007427993	0.015190245	0.349240163	0.379620654
93	313340834	0.291517419	0.051094456	0.009328529	0.019076841	0.272440578	0.31059426
94	33056908	0.214908843	0.024804532	0.004528667	0.009261124	0.205647719	0.224169968
95	3374201845	0.397305911	0.068037319	0.012421858	0.0254027	0.371903211	0.42270861
96	1822429448	0.006123322	0.001661913	0.000303422	0.000620499	0.005502823	0.006743821
97	314934291	0.116510114	0.029364878	0.005361269	0.010963794	0.105546319	0.127473908
98	1822429447	0.092694254	0.028888432	0.005274282	0.010785906	0.081908348	0.103480161
99	53166257	0.083464012	0.019013491	0.003471373	0.007098957	0.076365055	0.090562969
100	53166256	0.157978279	0.02569041	0.004690406	0.00959188	0.148386399	0.167570159

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VITA

Ebin Antony was born on 7th October 1993 in Thiruvambady, Kerala, India. He received his Bachelor of Technology degree in Electrical and Electronics Engineering from Hindustan Institute of Technology and Science in Chennai, India.

In 2015, Ebin began attending Missouri University of Science and Technology (Missouri S&T) in Rolla, USA. In July 2017, Ebin received a Master’s degree in Systems Engineering.