TRANSPORTATION INFRASTRUCTURE NETWORK PERFORMANCE ANALYSIS

by

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This thesis is dedicated to my mum Miss Augustina Coleman who encouraged me to keep pushing and not give up during trying times.

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ABSTRACT

The main objective of this thesis is to analyze the transportation infrastructure based on performance measures. In doing so, the abstract presents a transportation network as a system of nodes and links. It is important to identify critical components in transportation networks. In identifying critical components of the network, performance measures such as nodal degree, nodal closeness, nodal eigen vector, nodal betweenness, which are the most widely used were explored in the analysis of the network. These measures account for the vulnerability of a node to failure in the transportation network.

In our daily use of transportation networks, we are faced with disruptions that engender change in the transportation network. Disruptions tend to be commonplace in transportation systems. These include manmade disruptions such as accidents to natural disasters such as floods due to rainfall and hurricanes, seismic activities among others which are unprecedented. These incidents change how road users interact with the transportation system due to the disruptions that occur. The disruptions cause increased travel time, delays and even loss of property. These disruptions lead to direct, indirect and induced impacts.

This study provides a firsthand diagnosis of the vulnerability of the transportation network to flood by ranking the nodes using performance measures and multicriteria evaluation. The paper found out that various performance measures may produce different critical nodes but with the employment of sensitivity analysis and veto rule, the most critical node can be established The paper found out that node 80 is the most critical and essential node of the entire network after the impact of flood.

1. INTRODUCTION

1.1 Background and Problem Statement

There has been numerous research work put into modeling infrastructure network. Many real-world systems such as electricity, transportation, wind, biological systems, social interactions and many others can be represented by graphs. The term network can be explained as a graph: A graph is made up of nodes and links. Also, the arrangement of nodes and links in a network is referred to as the topology. A paper review from (X. Zhang, Miller-Hooks, & Denny, 2015) and (Everett & Borgatti, 2012) shows that the conventional way of analyzing a network is by using performance measures. Immense research has been geared towards studying the impact of critical nodes in a transportation network by using performance measures as metrics. There has also been research into the impact of vulnerable nodes in transportation network. These researches have sought to solve questions about:

- How to identify critical node
- Performance measures suitable for ranking nodes
- Impact of disruption in a network

Having knowledge of the solutions to these questions can be used by policy makers and planners to prepare cities around the world for the impact of possible disruptions and evacuation of flood prone zones in the future.

1.2 Research Motivation

The purpose of this research is to develop a methodology that exemplifies the impact of a transportation network due to a flood disruption and provides insight into what can be addressed in Kosciusko since that has not been tackled in research. Transportation systems are built to be functional and efficient. A breakdown in a link or node proliferates and causes adverse effects that affect the system. There is therefore the need to make transportation systems more resilient.

1.3 Research Significance

This research exemplifies the importance of critical nodes in the Kosciusko County and implications of disruption in a transportation infrastructure network. This research is designed to aid policy makers in the transportation industry to quickly identify critical nodes after disruption due to flood in a network and easy evacuation of residents in flood hazard zones. Insights of this paper would aid in adjustment planning, evacuation purposes during a disruption in the infrastructure network and making well informed decision by transportation engineers and policy makers by government for pre-disaster. For example, suppose a network is to be designated for expansion and a certain budget has been allocated, this research helps to know the exact node and associated links to invest in.

1.4 Thesis Organization

The thesis is divided into seven chapters. The First chapter introduces the topic. Chapter Two presents literature review on transportation network, network performance measures, impact of disruption and multicriteria evaluation. Chapter three focuses on the study area. Chapter four presents the methodology. Chapters five embraces the development of the network. Chapter six presents the results of the study. Finally, in Chapter seven, summary and conclusions based on the research findings are presented.

2. LITERATURE REVIEW

2.1 Introduction

A transportation system consists of a set of interconnected components which comprise of a set of vertex/nodes and a set of edges/links (Brijder, Harju, & Hoogeboom, 2012) that work together with the aim of fulfilling a service. The general way to delineate a network is to draw a dot for each node and join the two dots with a line to form a link(Diestel, 2000). For the purpose of this study, nodes represent intersections and links represent streets/highways. In our day to day activities network users are faced with disruptions such as flooding, work zones, accidents among other disasters at either nodes or intersections that affect the network. These delays are indicators that a transportation network does not have a fit design to meet the socio-economic needs of present and future users. These delays cause increases in fuel consumption and emissions pollution; vehicle ravaging over time (Antipova & Wilmot, 2012). These unforeseen events due to exponential increase in population and natural disasters are expected to rise in the imminent future(Suarez, Anderson, Mahal, & Lakshmanan, 2005). Several combination of performance measures have been used to measure the performance of nodes and links during these disruptions to help transportation planners and policy makers in decision making.

In this chapter we look at past research on graph theory, links, nodes, performance measures and the impact of disruptions in a network.

2.2 Transportation Network Performance

In (Likaj, Shala, Mehmetaj, Hyseni, & Bajrami, 2013), the researchers found a methodology to determine the optimal path between two points by using Dijsktra algorithm The result of the article showed that Dijkstra algorithm is an effective tool in determining the lowest cost in a network. This algorithm has similarities with betweenness performance measure.

(X. Zhang et al., 2015) investigates the resilience of 17 network structures: Grid, hub and Spoke, Double tree, Ring network, Matching pairs, Complete, Complete grid, Double U, Converging tails, Diverging tails, Diamond, Crossing path, Single depot, Random, Scale free and Small world. These network structures were quantified using throughput and connectivity as network performance measures. The general ranking of the network topologies from most resilient to least resilient was found to be: complete, matching pairs, complete grid, diamond, grid, single depot, central ring, hub-and-spoke, double-U, converging tails, random, scale-free, small-world, crossing path, double tree, diverging tails and ring network. The authors conclude that in all network topologies, improvements in all types of resilience are obtained from taking preparedness and/or recovery actions. The highest level is attained when both preparedness and recovery options are allowed. This result ties into the established researches that in transit systems, it’s more important to add new routes but to buttress this point, the incorporation of different modes of transit like the public transit would prove helpful.

(El-Adaway, Abotaleb, & Vechan, 2017) used the concept of Social Network Analysis (SNA) which is abstracted from graph theory to analyze transportation network in two scenarios in Jackson and Biloxi Gulfport both in Mississippi. The approach of this paper starts by drawing similarities between the language of SNA and transportation network like shortcuts, path redundancy and bridges. Furthermore, the Annual average daily traffic (AADT) traffic count data for the studied intersections were gathered, and key intersections were labeled using Google Earth so that the points could be easily tracked. The traffic count information was then input into adjacency matrices, with every intersection node input into both i and j directions and traffic counts input into the corresponding cells. Performance measure calculations were performed using UCINET software, which specializes in various types of SNA. Network diagrams were developed using NetDraw, a graphical visualization program in UCINET.A total of 56 nodes and 118 nodes were studied for Jackson and Biloxi respectively. It was observed that due to greater traffic density in downtown Jackson, node 42 had the highest betweenness performance while for Biloxi, nodes 40 and 53 had the highest betweenness because they represented bottlenecks through which all pathways must go to connect one side of the network to the other which corroborates with (Ghanbari, Jalili, & Yu, 2018) that traffic counts connected directly to a node greatly impact the node’s betweenness performance. A higher betweenness performance of a node leads to its susceptibility to failure.

This (Kumar, Haque, Mishra, & Golias, 2019) research, attempted to understand the relative criticality of links in a road network and suggest a methodology to rank the link according to three performance metrics (link volume, importance of facilities served, link betweenness). A small network of 18 links is piloted. The measures were altered that is increased and decreased to see the outcome of the links performance. The authors noted that with a budget of zero, link 9 ranked as most critical. However, when the budget allocation increased to 50 million, the most critical links were links 9 and 8 when previously link 14 occupied that position. Also, link performance changed significantly with each altering measure and hence not one metric is enough to analyze the network.

(Cantillo, Macea, & Jaller, 2019) proposed a framework for identifying critical links in a network and the cascading effect of a disruption on cost. A case study was carried out on Columbia, a coffee producing region that was hit by an earthquake. Travel time was used a metric for the links. The links with the highest travel times incurred the greatest costs.

Contrary to the findings of many researchers, (Akbarzadeh, Memarmontazerin, & Soleimani, 2018) suggested that central nodes though important to the urban transportation system, its disruption is not detrimental to the entire system. It further claims that betweenness centrality is not solely the determinant of a critical node. A case study of Isfahan and Anaheim was undertaken to support the claims. The results of the findings show that the failure of the critical node in an urban setting causes rerouting which follows the power law and hence betweenness centrality is more of functional merit than topological merit. In support of the previous claims of the afore mentioned paper,(Akbarzadeh, Memarmontazerin, Derrible, & Salehi Reihani, 2017) sought to demonstrate that node betweenness for (large scale) and the sum of capacities for its links contributes to node criticality. In this research, six different betweenness centralities were calculated: no weight, traffic flow, link length, travel time, congestion (ratio of traffic volume to link capacity), and the reciprocal of link capacity. To affirm the method, a case study was carried out on the urban street system of Isfahan Iran with 2150 nodes and 4760 links. It was observed that the results of betweenness centrality depend heavily of the type of link weights chosen (length as the link weights), the nodes located in the central part of the city have the highest betweenness performance. Though the paper found it surprising that with congestion as link weights, surrounding and relatively low-volume links have the highest betweenness centralities, I saw otherwise. This is because human decision making is necessary in route determination (Guo, Huang, & Wan, 2019).

(Panos, Ntantogian, Malliaros, & Xenakis, 2017) portrayed the interaction of a system of systems from the networking field. A blackhole attack compromises a router and leads to system breakdown. This follows a graph theory concept. The dynamic threshold cumulative sum was employed in order to detect abrupt changes by producing minimal rates of false positives.

In (Ahmadzai, Rao, & Ulfat, 2019) authors used a GIS based methodology which includes 3 steps. The first step being Data preparation, secondly Modelling/Generation of IGNRN, and lastly the authors measured three classes of performance, namely, closeness, betweenness and straightness. A case study was carried out on Kandahar City road network. It was observed that betweenness is integral in the identification of major roads in the network. (Amirhassan Kermanshah, Karduni, Peiravian, & Derrible, 2015)evaluated the resilience of networks after a disruption using GIS and network science approach. Betweenness centrality was used to measure the shortest path connecting nodes when there is a disruption. Before disruption the betweenness of the network was evenly distributed but after disruption, the link betweenness of network was skewed to the center of the network for the case study. After disruption, the network was separated into three isolated pathways with a drop in betweenness performance of 0.3% from 70%. This slight decrease in performance indicates the resilience of the network.

2.3 Impact of Disruptions

(Muriel-Villegas, Alvarez-Uribe, Patiño-Rodríguez, & Villegas, 2016) applies a framework to evaluate the vulnerability and reliability of a network under disruption in a developing country Subsequently in Antioquia, Columbia, the study found that during the rainy season, Antioquia’s primary road network is one of the most unreliable road systems. The author suggested that information about network disruptions during natural disasters should be accurately documented to facilitate research.

(Xu, Chen, Jansuwan, Heaslip, & Yang, 2015) sought and found two alternative methods in characterizing the redundancy of a network during a disruption. These two alternatives tackled the question of how many alternative routes are available during a disastrous event and the capacity (modes) on the redundant routes. A case study was carried out on Winnipeg network and it was concluded that the two alternatives complement each other in that adding a new route may not necessarily increase the capacity but also considering a different mode.

(Nyberg & Johansson, 2013) exemplify the use of windstorm as an indicator of the vulnerability of road network. The research points to the application of geographic data sets and GIS techniques for highlighting road networks that are susceptible to storm felled trees which lead to road closure. The methodology is applied to elderly people 80years+ with daily need of assistance following a severe storm. The road network of the municipalities had between 11 % and almost 20 % of the total length bordered by forests with tree height exceeding 20 m. Using these vulnerable road sections as closures in the network, the access to the population of advanced age in the municipalities was degraded to between 55 %. For a more detailed analysis a more sophisticated method could be explored.

It is worth noting in (Viljoen & Joubert, 2016) that the robustness of the global container shipping network is highly relevant for economic growth. This study uses targeted link disruption to investigate the vulnerability of the network. This article applies two strategies: the betweenness strategy and the salience strategy. After 10 iterations of 1113 nodes and 15916 links using the betweenness and salience disruption strategies, it was observed that the salience strategy reduces the sharing attributes of the critical path by 25% of the capacity while the betweenness reduces 75% of its capacity. It was concluded that the betweenness strategy is more effective in decreasing flexibility.

(Thacker, Pant, & Hall, 2017) explored the interoperability of national infrastructure which cannot be overlooked and exemplifies the consequence of failure in the domestic flight network that is interdependent on the electricity network. It demonstrates this using England and Wales as prime examples. The goal of the methodology is to provide new insights into unforeseen events and applied network disruption analysis. The methodology follows a mathematical approach to map the spatial and topological characteristics of critical national infrastructures across a range of scales. This includes a unique dataset of more than 160,000 nodes which represent airports and edges which represent airline routes. Connections are established between electricity network assets and airports through the addition of an edge that connects the airport to its nearest substation. Customer demand is used as weight for the edges. The findings show that following the disruption of a small number of electricity assets, failure is propagated throughout the network which affects customer service. Knowledge from this research helps in adaptation planning and decision making by policy makers.

(Amirhassan Kermanshah & Derrible, 2017) provides an interesting take on the robustness of road networks to extreme flooding events. It employs GIS properties, network topological indicators and information from U.S FEMA flood plains to simulate extreme flooding in New York and Chicago and measure variations in the number of trips before and after disruption. The first approach is to assume that the route of trips from households to jobs is the shortest path between origins and destinations. Therefore, this process represents the total number of trips completed before extreme flooding in a city. The total number of trips for New York City and Chicago were 2,686,918 and 212, 989 respectively. The next step was to categorize the total number of trips post flooding into 4. Namely trips completed by travelling the exact same path pre and post flooding, trips completed but forced to use longer paths, trips that could not be completed because the origin and destination cannot be reached and trips that could not be completed because the origin and destination are in floodplain. From these categories, five metrics where defined (A. Kermanshah & Derrible, 2016). The results from New York showed that 53.26% accounted for decrease in uncompleted trips but the network still offered 17% of alternative routes after disruption while in Chicago, 20% of trips were not completed after disruption. It was observed that Chicago has a higher robustness as compared to New York since only 4% of its trips had to use longer paths as opposed to 17%.

(Zeng et al., 2019) focuses on the land use effect on the optimization of spatial distribution of infrastructure. Due to the exponential growth in population, Wuhan a central business point in China has had its road network greatly impacted. The paper focuses on 48 point of interest (nodes) and lines (road network leading to the nodes). The embedded spatial influence using the gravity model was measured. The gravity model helps with the determination of volume of flow between two or more points.

2.4 Multicriteria Evaluation

It is important to apply the optimal performance measure to the transportation network for efficiency and sustainability. (Awasthi, Omrani, & Gerber, 2018) employed a multicriteria approach which involved the application of fuzzy TOPSIS, fuzzy VIKOR, and fuzzy GRA that rank three projects in the city center of Luxembourg. The three projects are implementation of a new tramway(A1), re-organization of existing bus lines in the city to perform optimized service (A2), and implementation of electric vehicle car-sharing stations in the city (A3) The methodology involves four steps. The steps include, identification of criteria for sustainability evaluation of urban mobility projects, setting up a board for decision making due to lack of quantitative data, application of fuzzy TOPSIS, fuzzy VIKOR and fuzzy GRA to rank the alternatives and finally a rule used to select the best alternative. The authors employed the fuzzy technique because of inadequate quantitative data available since the project is one of the first in investigating multicriteria decision making to urban mobility projects under uncertainties. VIKOR uses cityblock distance metric whereas TOPSIS and GRA used Euclidean distances. From the fuzzy GRA analysis, A1>A2>A3, from fuzzy topsis A2.>A1>A3 and from fuzzy VIKOR A3=A1=A2. The authors selected alternatives A1 and A2 using the veto rule because they ranked highest twice in two analysis. They further used sensitivity analysis to select alternative A1 since it scored the highest votes of 22.

Like the above paper, the authors (Curado, Tortosa, Vicent, & Yeghikyan, 2020) examined three centrality measures namely the Adapted PageRank algorithm modified (APAM1), the Adapted PageRank algorithm modified (APAM2) and the CVP were applied to a real complex transportation system in Italy, Rome. The centrality measures produced different results for important vertices in the network. To eventually find the most important vertex in the network, the centrality measures were compared against each other using the most usual correlation coefficients (Spearman, Pearson and Kendall) It was observed that the three correlation values showed strong similarities of 98% which is close to one and hence they are similar measures.

This paper by (Xu Zhang, Zhang, & Lee, 2020) focuses on the importance of ranking the logistic nodes of China railway express network. This was done by the structural hole method which uses six indicators namely, degree, network constraint, network grade, network scale, efficiency, and clustering coefficient to evaluate the complex network. In conclusion, Moscow ranked number one which shows its relevance in the China railway express network and the vulnerability of that node to attack and its impact on the entire network.

2.5 Chapter Summary

This chapter summarizes graph theory, network topology, performance measures and impact of disruptions. The following chapter focused on the study area of this study.

3. CASE STUDY

3.1 Introduction

The state of Indiana is susceptible to floods caused by flash flooding, river flooding, tropical systems, coastal flooding, snow melts and dam breaks. Kosciusko County is among the 20 counties (Allen , Benton, Carroll, Cass, DeKalb, Elkhart, Fulton, Huntington, Jasper, Kosciusko, LaPorte, Lake, Marshall, Newton, Noble, Pulaski, St. Joseph, Starke, Tippecanoe, White and Whitley) heavily affected by floods declared by the Federal Emergency Management Agency (FEMA). The county has been declared by as FEMA as Special Flood Hazard Area (SFHA) declared by FEMA in, May 2018. The Special Flood Hazard Area (SFHA) is an area that would be inundated by flood having a 1-percent chance of being equaled or exceeded in any given year(County, Areas, & County, n.d.). The Kosciusko county has experienced severe flooding in recent time and this pattern is probable to recur.

3.2 Study Location

Kosciusko County is a county located in the U.S. state of Indiana. Census 2010 recorded the population at 77,358.The county seat is Warsaw. The county was formed in 1836. It was named after the Polish general Tadeusz Kosciuszko who served in the American Revolutionary War and then returned to Poland. The county seat is named after Warsaw, the capital of Poland.

3.2.1 FEMA Flood Plains

For the purpose of standardization, the base line probability which is also called the base flood (it is so called since probabilities and statistics can be baffling) is followed. Other terms used interchangeably for base flood include “100-year flood,” and “one-percent annual chance flood”. FEMA contains the nationally accepted 100-year flood plains which is used for flood insurance and management purposes by FIS and Federal Agencies in the USA. Through hydrologic analyses and hydraulic studies, flood elevations, velocities, and floodplain widths at each cross section for a range of flood flow frequencies are determined. These elevations are the main source of data used by engineers to generate the floodplain. The flood plains are superposed with road network and the affected nodes and links are taken out.

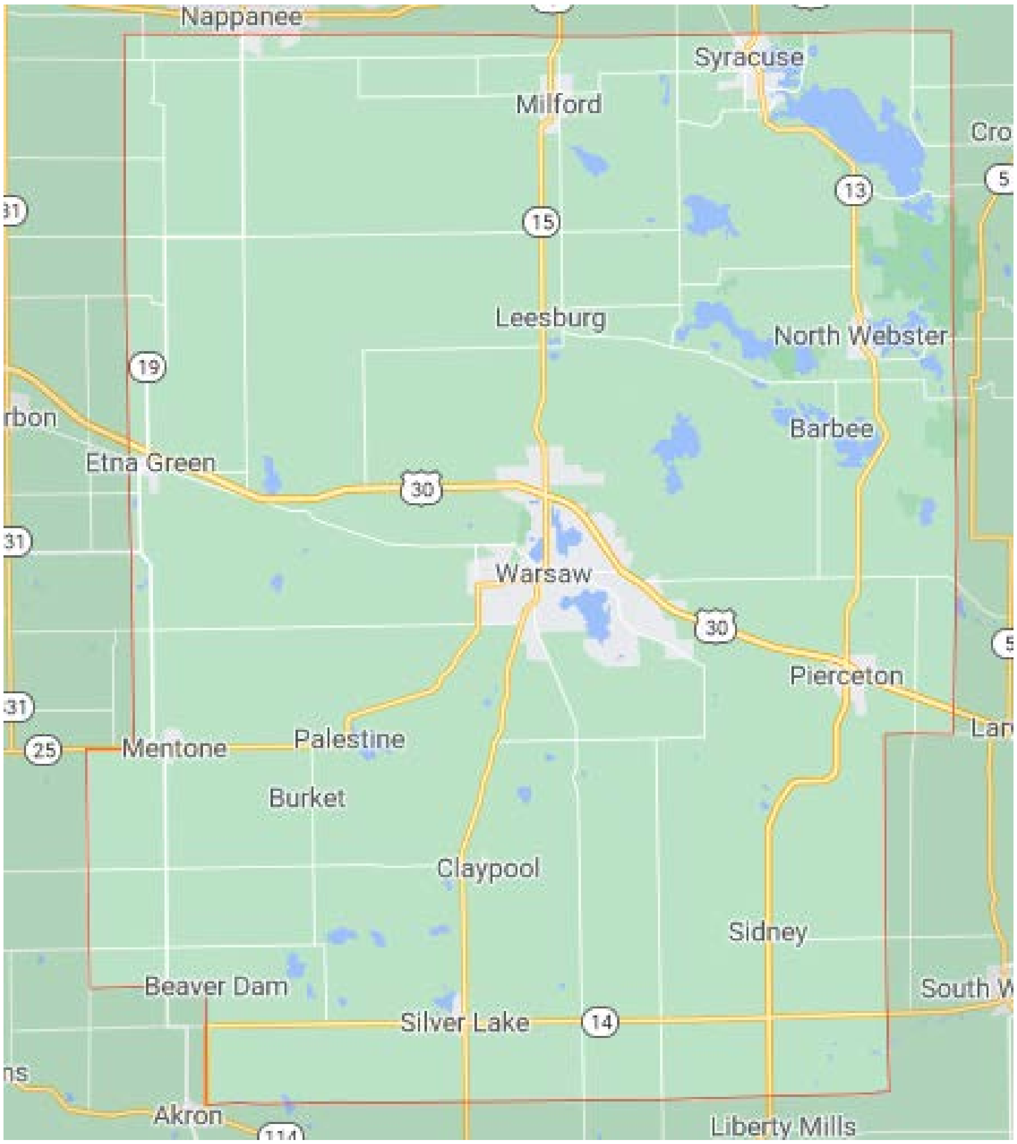

Figure 3.1 An aerial map of Kosciusko County

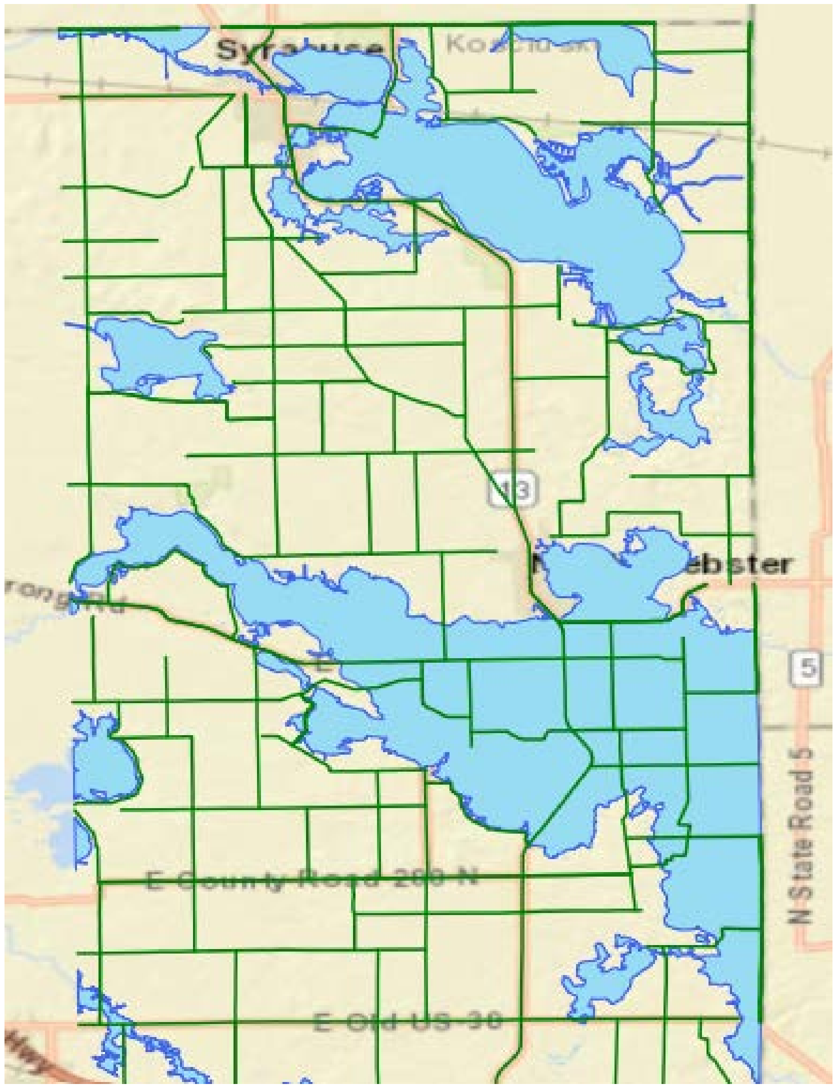

Figure 3.2 Flood area map of Kosciusko County

3.3 Chapter Summary

This chapter provided the description of the study area. Its location and boundary area can be seen from the above chapter. The next chapter will talk about the methodology followed to analyze the transportation network.

4. METHODOLOGY

4.1 Introduction

Flooding in Indiana is a not “if “situation but “when”. Given the number of major rivers and tributaries that dissect Indiana and the fact that approximately 24 percent of the state was historically covered by wetlands, much of Indiana is susceptible to severe flooding. The framework of this study outlines a deterministic approach in tackling a flood disruption in the Kosciusko county transportation network.

4.2 Framework

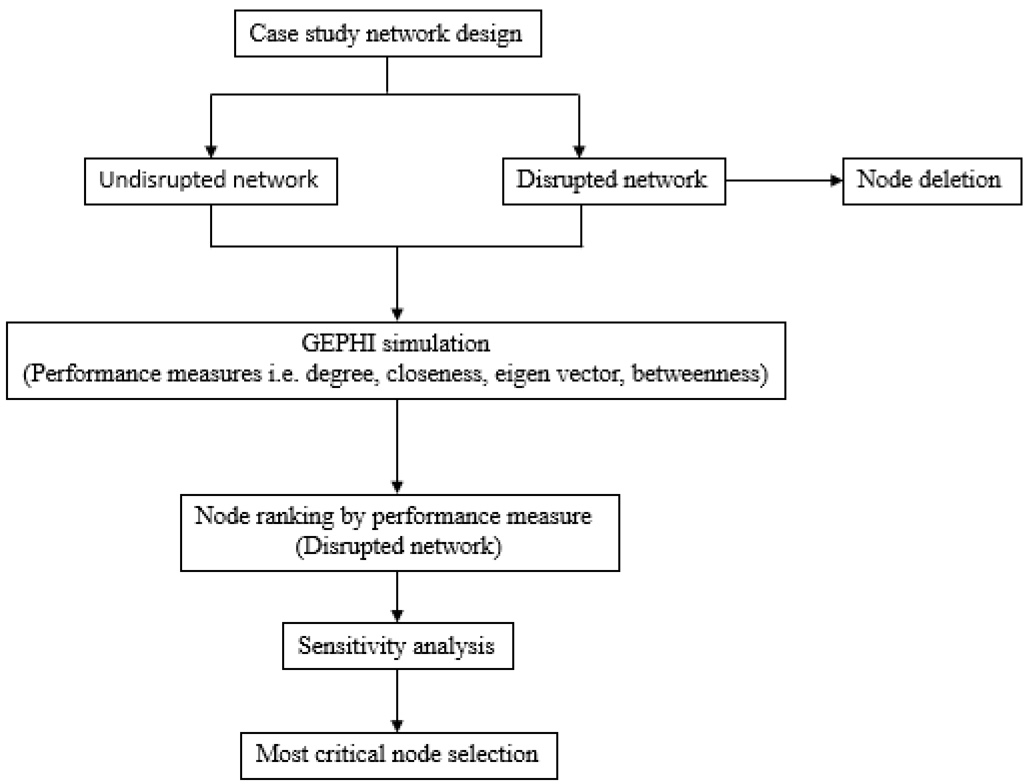

Figure 4.1 Most critical node identification methodology

4.3 Chapter Summary

In this chapter a detailed step by step process of how to tackle the problem of the study area is outlined. The next chapter focused on the development of the network.

5. NETWORK DEVELOPMENT

5.1 Introduction

A network in its simplest form is a connection of two points. The points being the nodes and the line joining them, the link. Networks in the real-world systems such as electricity, world wide web, food web, transportation and social network to name a few.

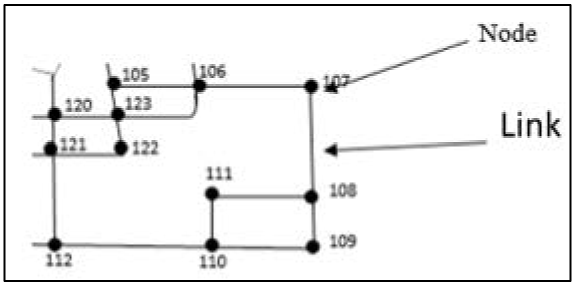

Figure 5.1 A small network composed of 12 nodes and 20 links

Table 5.1 Links and Nodes in networks. Example of real-world systems

Network	Link	Node
Electricity	Transmission line	Substation
World wide web	Hyperlink	Webpage
Transportation	Roadway	Intersection
Food web	Predation	Species
Social network	Ties	Actors

To further examine transportation networks, it is important to understand directed networks. Directed network is a graph in which each link has a direction pointing from one node to another node. They can be represented by lines with arrows on them.

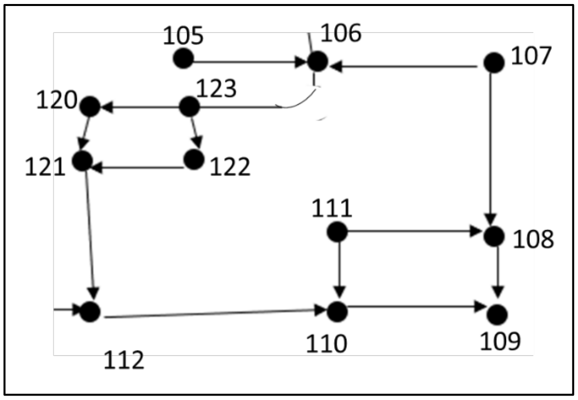

Figure 5.2 A small directed network with arrows showing the direction of the links.

5.2 Road Network Design of Study Area

The GIS interface allows you to search for addresses in the inbuilt map. Using the inbuilt map, the study area was located from FEMA, and a road layout superimposed using the road editor toolbox. The road editor toolbox provides all the important functionalities to create a road network as closely as possible to the existing roadway. The nodes and links for the network were established. The research aimed to assess the impacts of flood hazard zones on major roads in the network. Figure 5.3 shows the network generated for the study area.

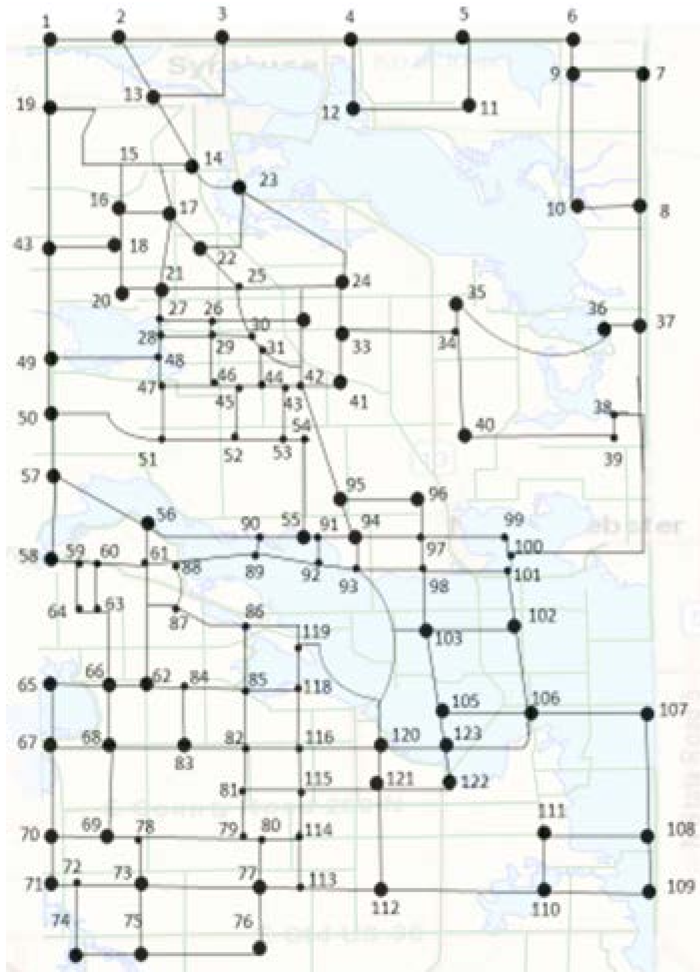

Figure 5.3 Developed network superimposed on flood map

5.3 Node Deletion

For this study, a total of 34 affected nodes were deleted to create the disrupted network. This was done due to the map being overlaid with the flood map. In effect the affected nodes were deleted. The deletion of nodes follows the theory that the node will not be returned after it is taken out. Node deletion is done to test the resilience of the network to disruption. Potential influential nodes can be uncovered with this process.

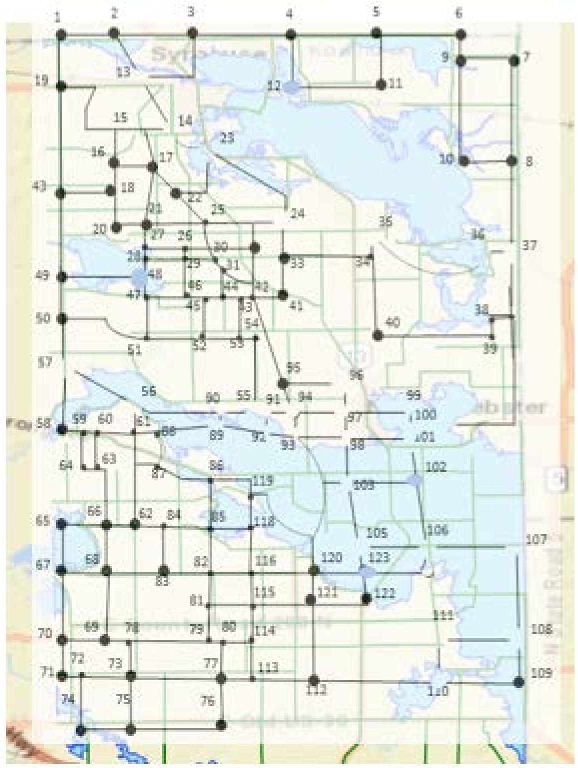

Figure 5.4 Developed network superimposed on flood map with deleted nodes

5.4 Application of Performance Measures

Several years ago, Alexander Bavelas a prolific researcher was influential in the concept of centrality measures in a network structure. Many years later, and with the advancement of technology, network simulation tools have been developed to identify influential actors in a network have improved how things work in the transportation industry tremendously. Especially due to its usefulness in reflecting what is happening in real life in our transportation systems to provide predictions for both long-term and short-term transportation planning and evacuation using data collected about the current system.

5.4.1 Nodal Degree

It is illuminating to know that a large volume of research has been invested in performance measures of transportation networks with Degree being one of the important measures in research. Degree is the number of links connected to a node. It is a simple and efficient performance measure which is very useful in analyzing a network according to (Chen, Lü, Shang, Zhang, & Zhou, 2012). It is worth noting that a central node is not necessarily at the center of the graph physically. Also, a node with high degree centrality is in a position to distort the channeling of information(Liu, Wei, Du, Xiao, & Deng, 2016). The degree of node k denoted by $C_D(P_k)$

$$C_D(P_k) = \sum_{i=1}^{n} \alpha\,(P_i, P_k) \qquad (3)$$

Where n is the number of nodes in the network and $\alpha(P_i, P_k) = 1$, if and only if node i and k are connected

Otherwise $\alpha(P_i, P_k) = 0$

Below for this example in Figure 5.2 showing its degrees.

Table 5.2 Illustrating degree of a node of **Error! Reference source not found.**Figure 5.2

Node	Degree
105	1
106	4
107	2
108	3
109	2
110	3
111	2
112	3
120	2
121	3
122	2
123	3

5.4.2 Nodal Closeness

Average distance of a node to other nodes in a network. It is calculated by the inverse of the sum of a node to other nodes in a network. It can also be viewed as the inverse of farness of a node to other nodes. Farness in this case is the sum of a distance of a node to other nodes(Abbasi, Hossain, & Leydesdorff, 2012). The closeness of a node k is denoted by

$$C_C(P_k) = \sum_{i=1}^{n} d(P_i, P_k)^{-1} \qquad (4)$$

Where $d(P_i, P_k)$ is the shortest paths linking $(P_i, and P_k)$

5.4.3 Nodal Eigen vector

The eigen vector measures the importance of a node based on the extent to which it is connected to other influential nodes. This shows how the centrality of adjacent nodes contributes to the overall centrality of the studied node. This means that a node with high eigen vector is adjacent to nodes with high scores(Borgatti, 2005). The defining equation of an eigen vector is denoted as

$$\lambda v = Av \qquad (6)$$

Where A is the adjacency matrix

λ is a constant

v is the eigen value

5.4.4 Nodal Betweenness

Betweenness quantifies the times a node acts as a bridge along the shortest path between two other nodes. Basically, it is a measure of the influence of a node over dispersing information throughout the network. Betweenness performance measure is centered on random walks(Newman, 2005). This has a similarity to the Travelling salesman problem which states one must find the cheapest cost in travelling to n cities and returning to the starting point such that each city is visited once(Bertazzi & Maggioni, 2014). A high betweenness centrality of a node implies that the node plays a major role in the network and any impact of that node causes a disruptive effect across the network due to the interdependency of other nodes (Krackhardt, 1996).

The betweenness centrality of node i, denoted by $C_B(i)$ is

$$C_B(i) = \frac{g_{jk}(i)}{g_{jk}} \qquad (5)$$

g_{jk}=the number of shortest paths between nodes j and k

$g_{jk}(i)$ = the number of those shortest paths that go through node i

5.5 Ranking of Performance Measures

In order to rank the nodes of the four performance measures from critical node to the least critical node, the following was done. The variables used in the excel function.

$$D_{vf_{n=x}} = \frac{D_{v_{n=x}}}{V_{h,d}} \text{ x } 100 \qquad (6)$$

$D_{v_{n=x}}$ = degree value for node

x = nodal number

$D_{vf_{n=x}}$ = value function for degree

$V_{h,d}$ = highest value for degree

$$C_{vf} = \frac{C_{v_{n=x}}}{V_h} \text{ x } 100 \tag{7}$$

$C_{v_{n=x}}$ =closeness value for node

x = nodal number

$C_{vf_{n=x}}$ = value function for closeness

$V_{h,c}$ = highest value for closeness

$$E_{vf} = \frac{E_{v_{n=x}}}{V_h} \text{ x } 100 \tag{8}$$

$E_{v_{n=x}}$ =eigen vector value for node

x = nodal number

$E_{vf_{n=x}}$ = value function for eigen vector

$V_{h,e}$ = highest value for eigen vector

$$B_{vf} = \frac{B_{v_{n=x}}}{V_h} \text{ x } 100 \tag{9}$$

$B_{v_{n=x}}$ = betweenness value for node

x = nodal number

$B_{vf_{n=x}}$ = value function for betweenness

$V_{h,b}$ = highest value for betweenness

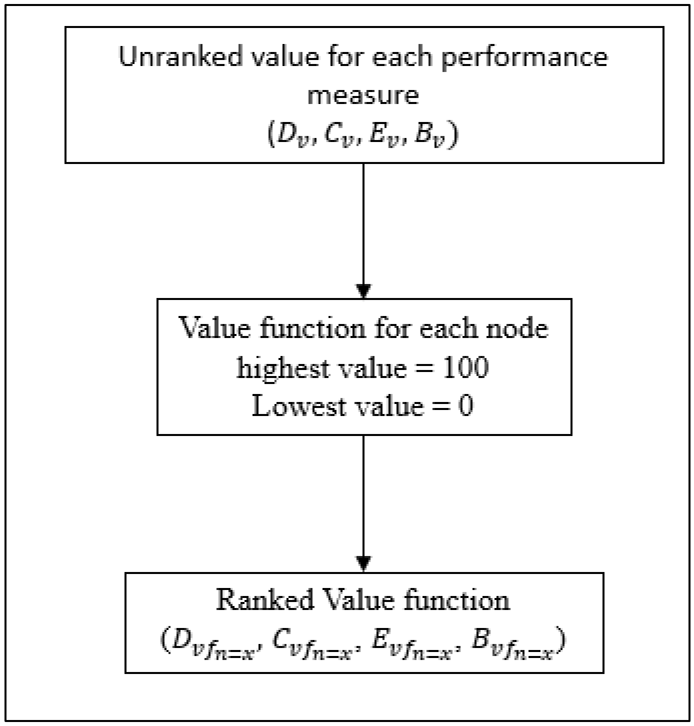

Figure 5.5 Ranked results of performance measures methodology

5.6 Sensitivity Analysis on Disrupted Network

The following formulae were used in obtaining the most critical node. For this purpose, five (5) case scenarios were studied

1. Case1: uniform weight factors were applied to the value function of each performance measure.

$$D_{vf_{n=x}} x0.25 + C_{vf_{n=x}} x0.25 + E_{vf_{n=x}} x0.25 + B_{vf_{n=x}} x0.25 \quad (10)$$

Table 5.3 Weight factors for Case 1

PERFORMANCE MEASURE	WEIGHT FACTOR
Degree	0.25
Closeness	0.25
Eigen Vector	0.25
Betweenness	0.25

2. Case 2: non-uniform weight factors were applied to the value function keeping degree as priority

$$D_{vf_{n=x}} x0.4 + C_{vf_{n=x}} x0.2 + E_{vf_{n=x}} x0.2 + B_{vf_{n=x}} x0.2 \quad (11)$$

Table 5.4 Weight factors for Case 2

PERFORMANCE MEASURE	WEIGHT FACTOR
Degree	0.4
Closeness	0.2
Eigen Vector	0.2
Betweenness	0.2

3. Case 3: non- uniform weight factors were applied to the value function keeping closeness as priority

$$D_{vf_{n=x}} x0.25 + C_{vf_{n=x}} x0.4 + E_{vf_{n=x}} x0.2 + B_{vf_{n=x}} x0.2 \quad (12)$$

Table 5.5 Weight factors for Case 3

PERFORMANCE MEASURE	WEIGHT FACTOR
Degree	0.2
Closeness	0.4
Eigen Vector	0.2
Betweenness	0.2

4. Case 4: non-unif0rm weight factors were applied to the value function keeping eigen vector as priority

$$D_{vf_{n=x}} x0.2 + C_{vf_{n=x}} x0.2 + E_{vf_{n=x}} x0.4 + B_{vf_{n=x}} x0.2 \quad (13)$$

Table 5.6 Weight factors for Case 4

PERFORMANCE MEASURE	WEIGHT FACTOR
Degree	0.2
Closeness	0.2
Eigen Vector	0.4
Betweenness	0.2

5. Case 5: non-uniform weight factors were applied to the value function keeping betweenness as priority

$$D_{vf_{n=x}} x0.2 + C_{vf_{n=x}} x0.2 + E_{vf_{n=x}} x0.2 + B_{vf_{n=x}} x0.4 \quad (14)$$

Table 5.7 Weight factors for Case 5

PERFORMANCE MEASURE	WEIGHT FACTOR
Degree	0.2
Closeness	0.2
Eigen Vector	0.2
Betweenness	0.4

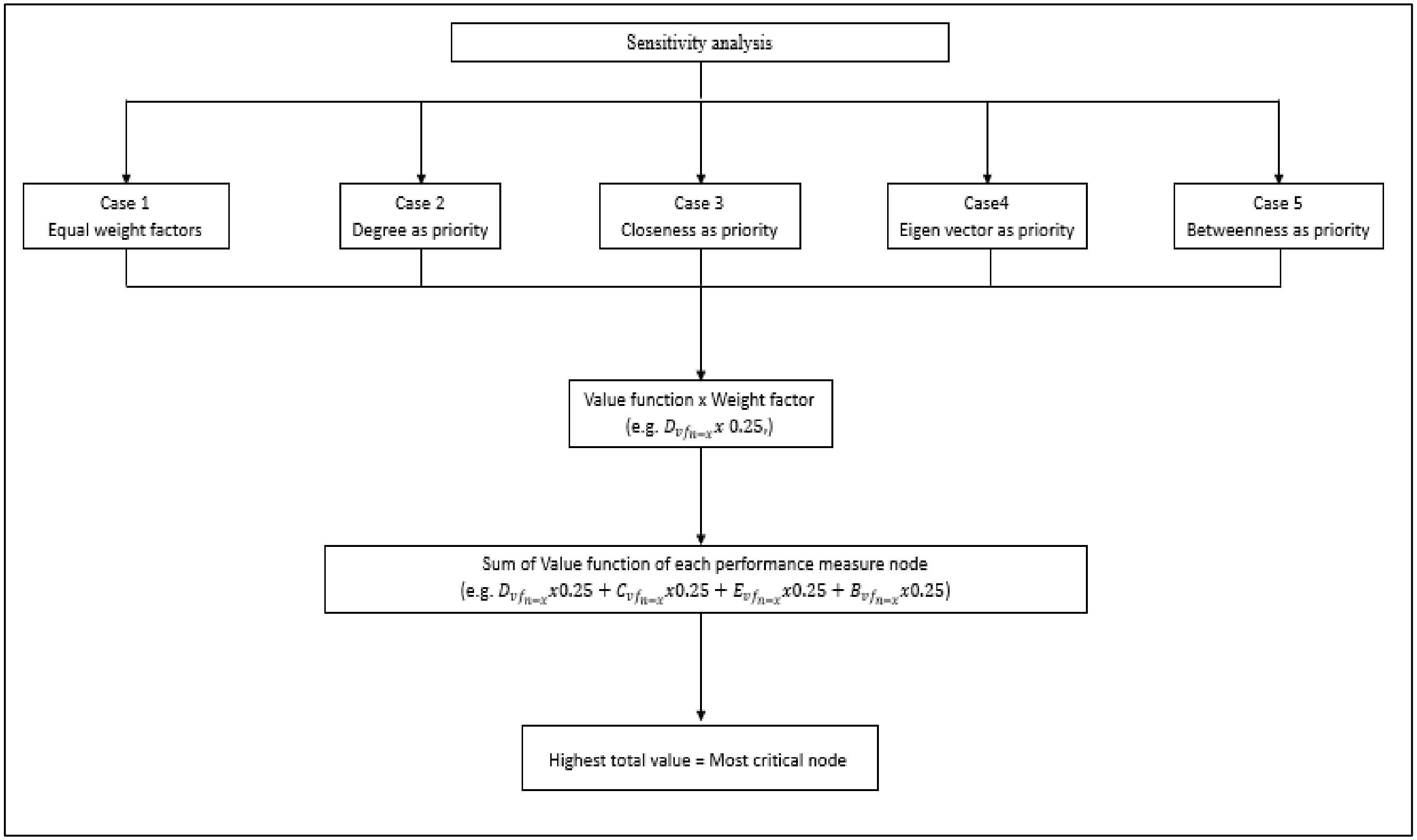

Figure 5.6 Sensitivity analysis methodology

5.7 Chapter Summary

This chapter summarizes the network development process. Data was collected from FEMA flood site, and network was developed using GIS, four performance measures (nodal degree, nodal closeness, nodal eigen vector and nodal betweenness) were applied using GEPHI simulation and finally ranking of nodes to select critical node using multicriteria evaluation

6. RESULTS AND DISCUSSION

6.1 Results from GEPHI Simulation

The network simulations were conducted using GEPHI. This simulation tool is a good visualization software package. A series of simulations are conducted for two (2) scenarios and the average results for the simulations are used for the analysis. In this research, eight (8) simulation runs are conducted for the four (4) performance measures. The scenarios were

1. A road network free of disruptions
2. A road network with disruption

Disruption defined in this research is flood affected nodes and links in the transportation network during the period of simulation.

6.1.1 Impact on Nodal Degree

The result of the difference in nodal degree is shown in **Error! Reference source not found.**. The transportation networks, nodal degree significantly reduces after the deletion of nodes and links. Before disruption, 1.64% of the system had a nodal degree of 4, 29.51% with nodal degree of 3, 60.66% with nodal degree of 2 and 8.2% with nodal degree of 1. After disruption, the system's result has sharply decreased. The disrupted network shows 0.87% with degree of 4, 15.65% with degree of 3, 55.64% with degree of 2 and 27.83% with a degree of 1. Overall, the network shows that nodal degree has reduced by 0.77%,13.86%and5.02% for nodal degree of 4,3 and 2 while it has increased by 19.63% for nodal degree of 1.

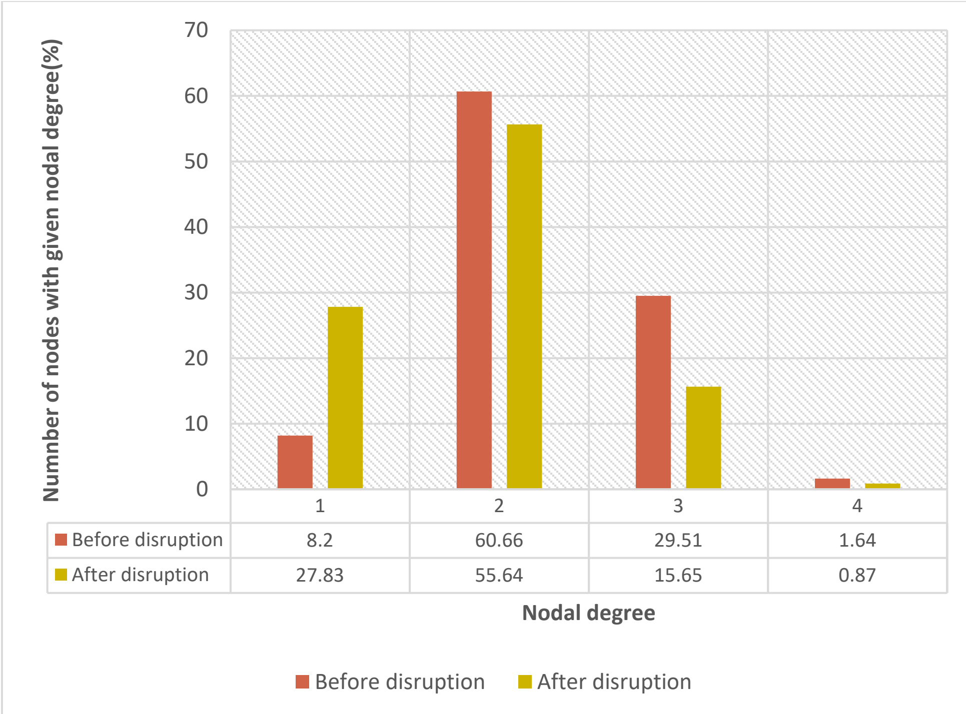

Figure 6.1 Summary of Nodal degree performance

6.1.2 Impact on Nodal Closeness

The nodes exhibited different nodal closeness results after simulation. Prior 15 nodes ranked first for critical nodes to disruption however, after disruption, 25 nodes ranked first as critical nodes.

Figure 6.2 shows the four critical nodes before and after disruption. It is evident that after disruption the number of critical nodes increase.

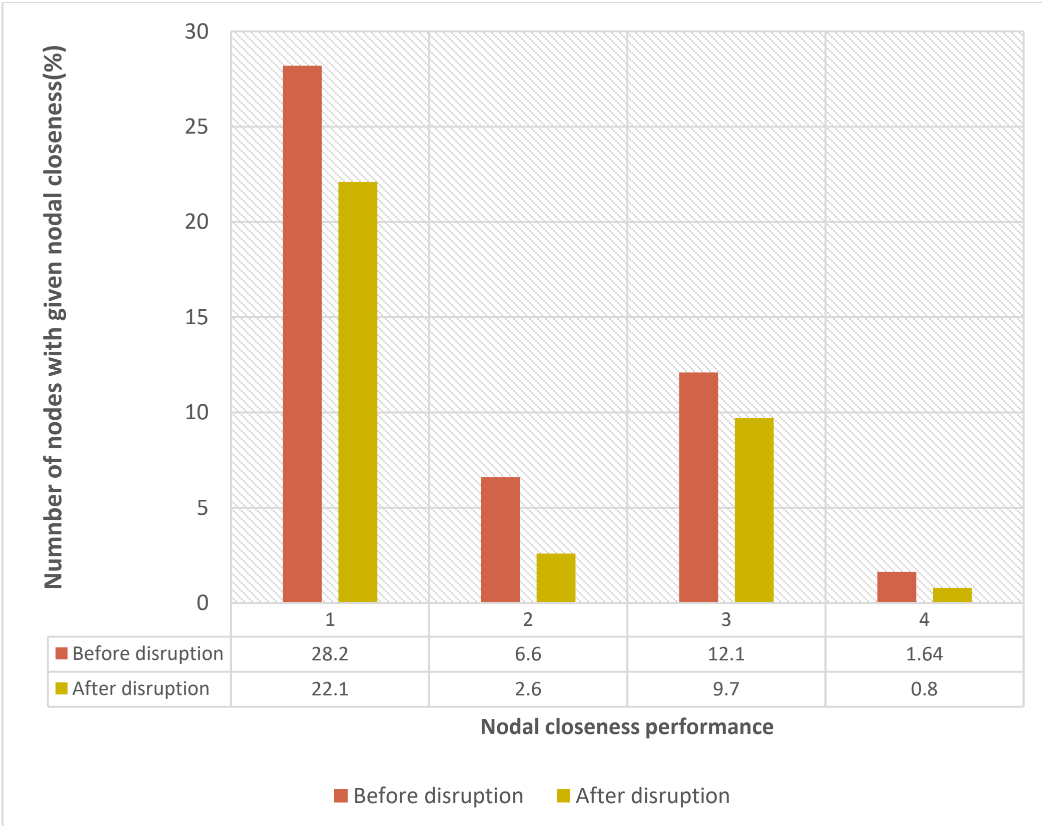

Figure 6.2 Summary of Nodal closeness performance

6.1.3 Impact on Nodal Eigen Vector

The nodes exhibited different nodal eigen vector results after simulation. Prior 10 nodes ranked first for critical nodes to disruption however, after disruption, node 48 ranked first as critical nodes.

Figure 6.3 shows the four critical nodes before and after disruption. It is evident that after disruption the number of influential nodes increase.

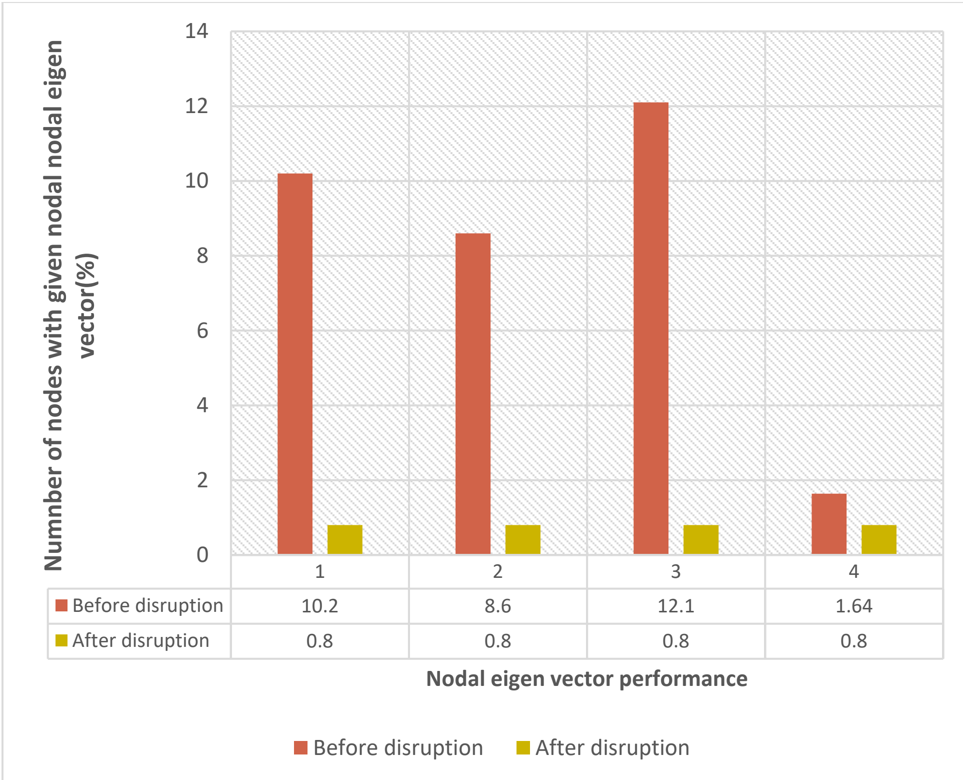

Figure 6.3 Summary of Nodal eigen vector performance

6.1.4 Impact on Nodal Betweenness

The nodes exhibited different nodal betweenness results after simulation. Prior 10 nodes ranked first for critical nodes to disruption however, after disruption, node 5 ranked first as critical nodes.

Figure 6.4 shows the four critical nodes before and after disruption. It is evident that after disruption the number of influential nodes increase.

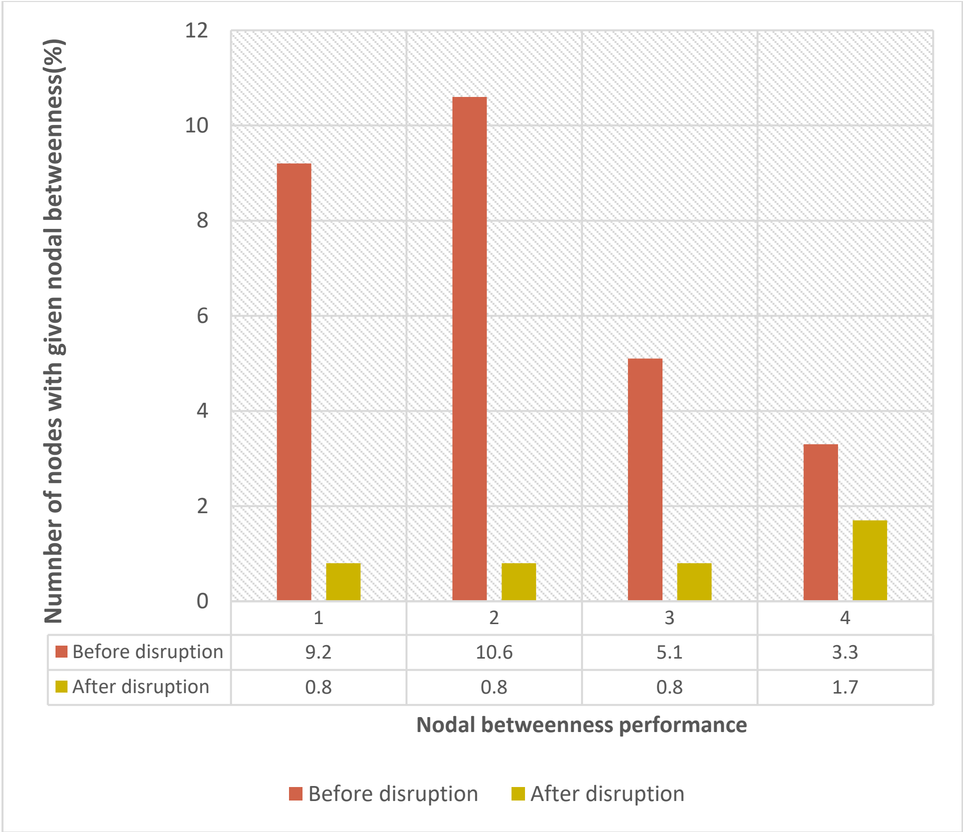

Figure 6.4 Summary of Nodal betweenness performance

6.1.5 Performance Measures Node Ranking

It is quite interesting to note that in all four performance measures ranking of nodes, a different node ranked first and the number of nodes that ranked first may be one or more. Looking at the case of closeness performance measure, it is evident that 25 nodes forming 22.1% of the data ranked first for critical node. 0.6% of the data ranked first for critical node for degree, eigen vector and betweenness.

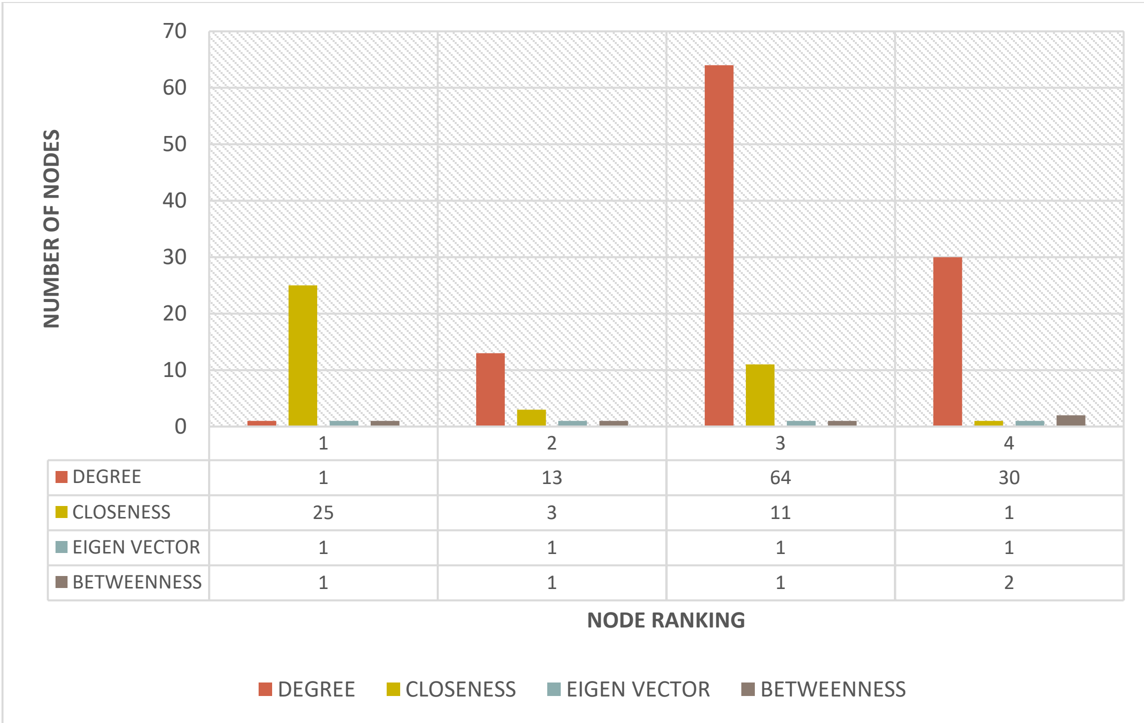

Figure 6.5 Result of Performance Measures Node Ranking

6.1.6 Impact of Sensitivity Analysis

The 10 most influential nodes in the five case scenarios were analyzed. For the five (5) case scenarios that were studied, node 80 ranked first as the most critical node in Case 1, Case 2, Case 3, and Case 4. For Case 5, node 7 ranked first as the most critical node though it ranked third place in Cases 1,2, and 3. Node 44 ranked second place in Cases 1,2,3, 4 and third place in Case 5.

Figure 6.6, Figure 6.7, Figure 6.8, Figure 6.9, Figure 6.10 and Figure 6.11 show how the network characteristics change in cases 1, 2, 3, 4 and 5 for the four performance measures for the five case scenarios.

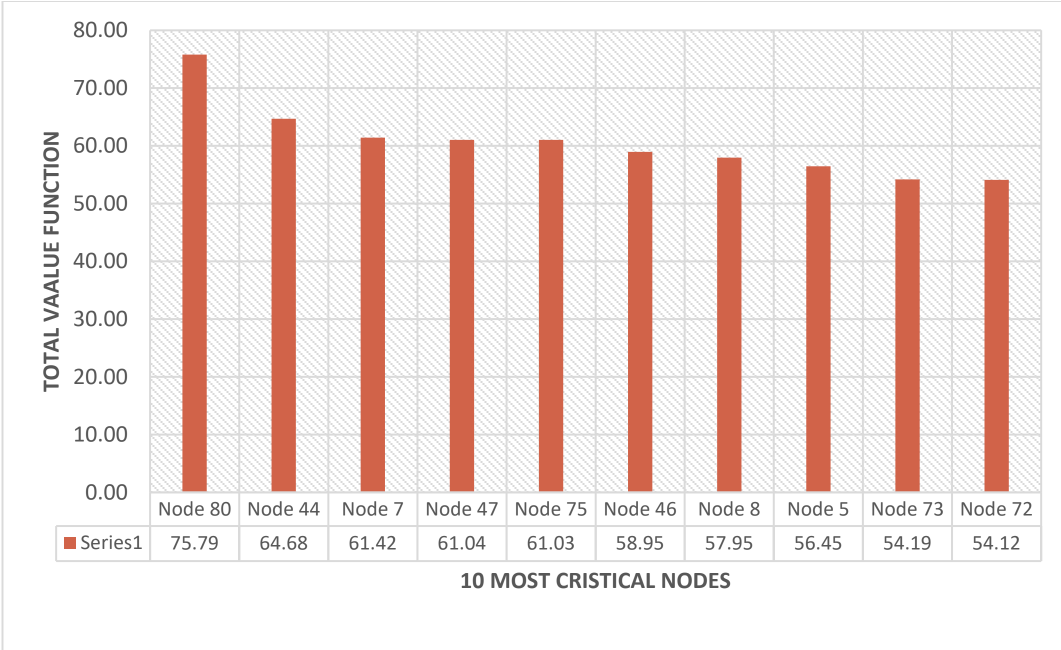

Figure 6.6 Case 1 nodal ranking

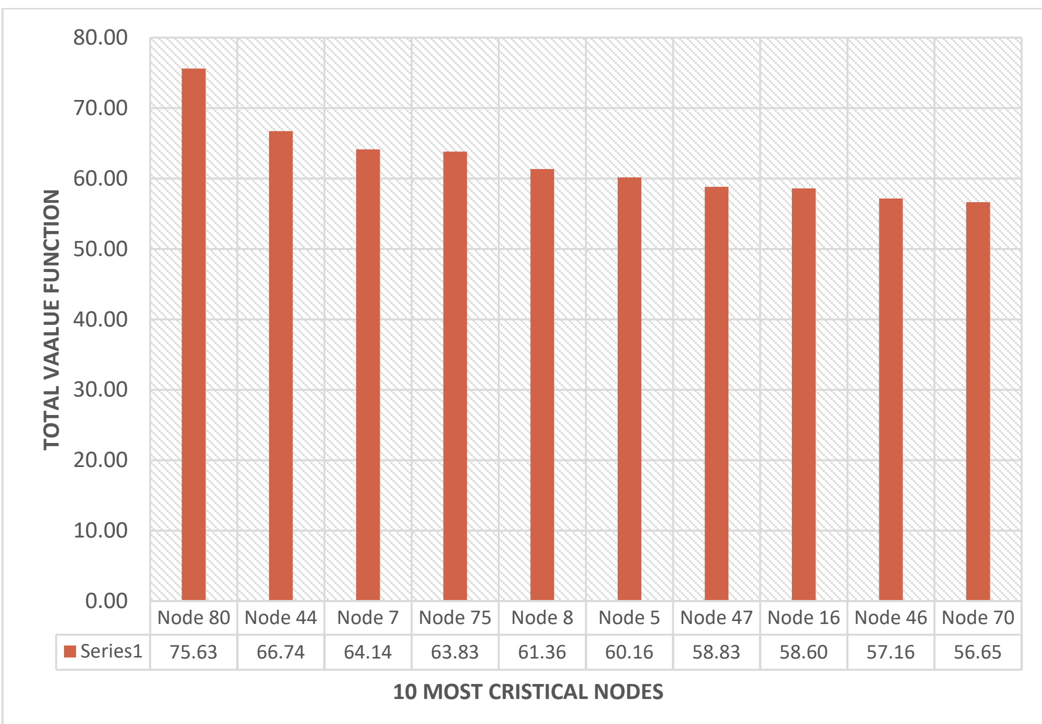

Figure 6.7 Case 2 nodal ranking

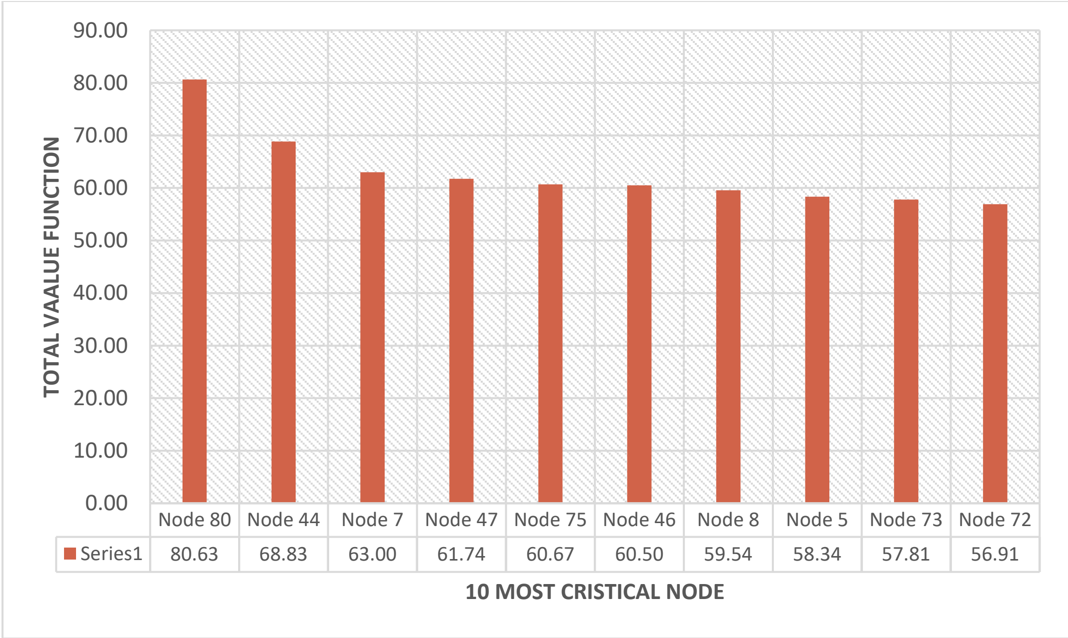

Figure 6.8 Case 3 nodal ranking

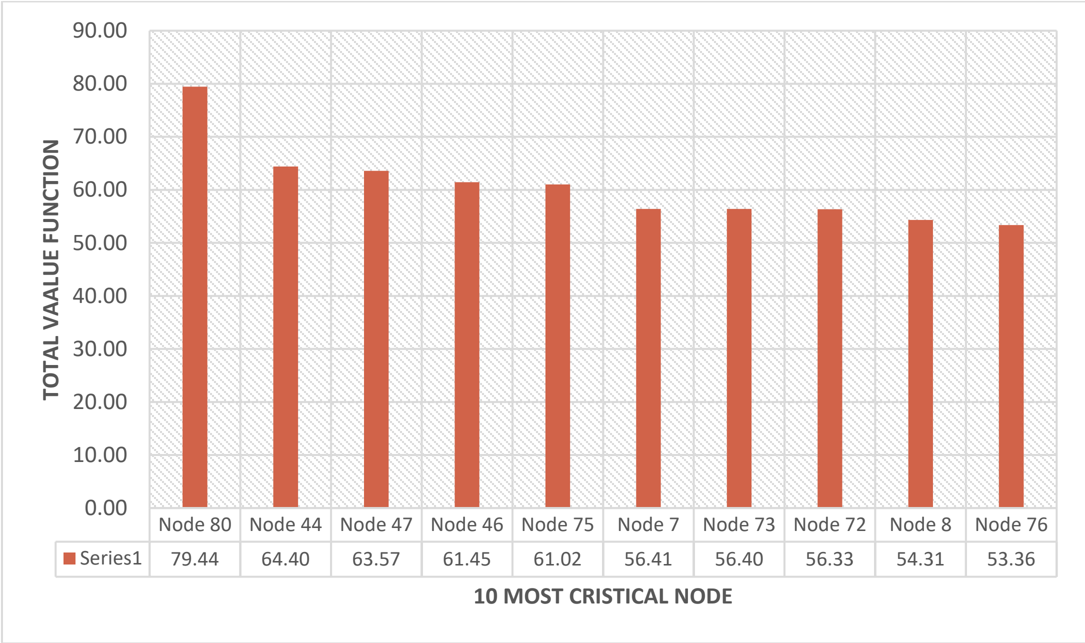

Figure 6.9 Case 4 nodal ranking

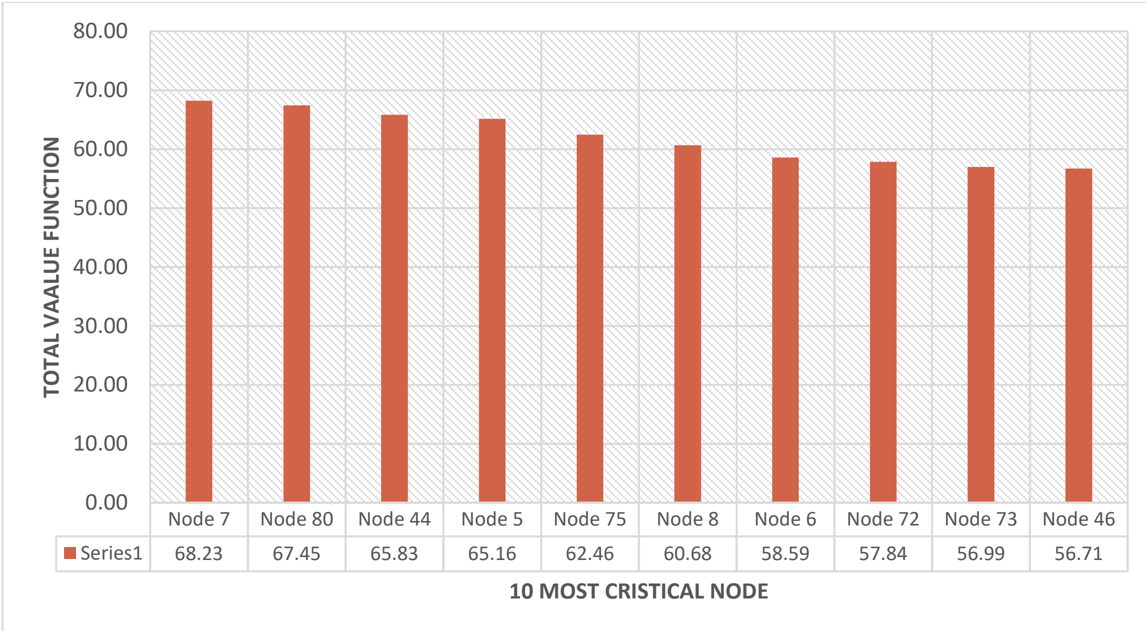

Figure 6.10 Case 5 nodal ranking

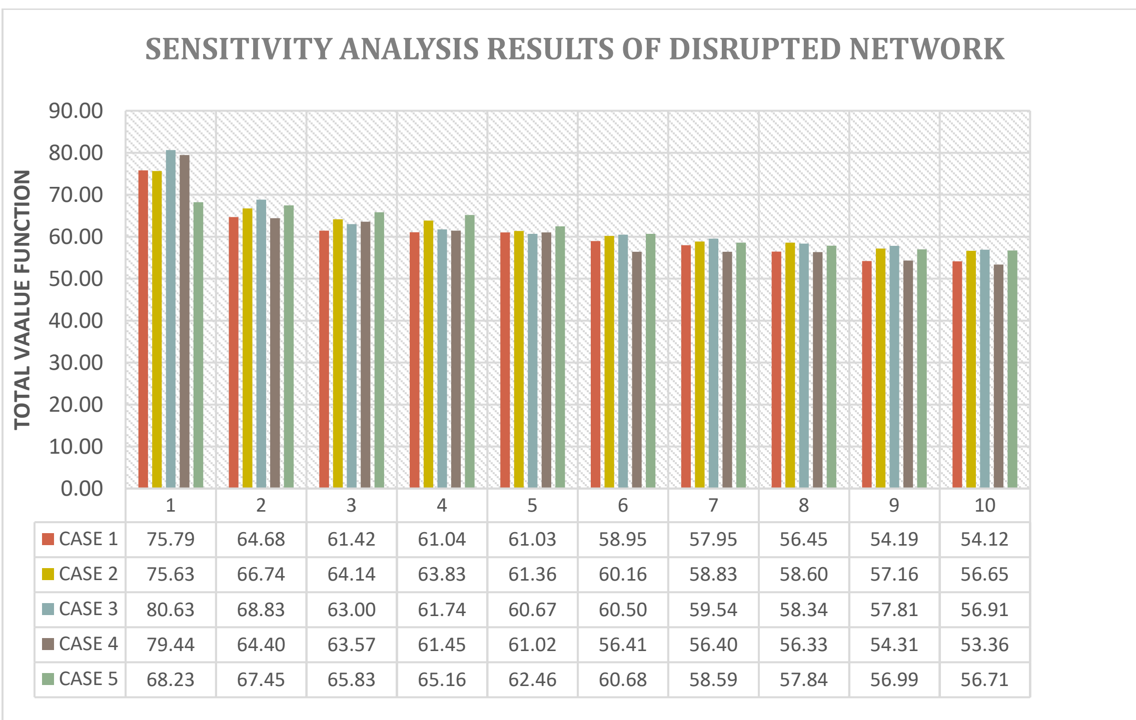

Figure 6.11 Summary of sensitivity analysis of performance measures with 5 case scenarios

6.1 Chapter Summary

123 nodes and 137 links were established before disruption while 89 nodes and 110 links after node and link deletion. The performance measures namely degree, closeness, eigen vector and betweenness were applied to the undisrupted and disrupted network and results analyzed. Also, the nodes were ranked accordingly for the undisrupted network and sensitivity analysis was carried out in 5 case scenarios in order to select the most frequent critical node in all cases.

7. SUMMARY AND CONCLUSION

7.1 Summary

For a considerable time now, researchers have devoted attention to finding different performance measures effective in quantifying the importance of a node in a transportation network. Four performance measures are compared by means of real network and real data on the Kosciusko county Indiana.

First and foremost, the network was developed following a systematic approach. This approach entailed identifying flood hazard zones from FEMA using GIS, collecting data on the distance, of the network. Also, flood affected nodes and links in the developed network of Kosciusko county were established.

Secondly, the employment of GEPHI, a network visualization tool in analyzing how each node performed before and after disruption of the network by applying performance measures (nodal degree, nodal closeness, nodal eigen vector and nodal betweenness).

Finally, the nodes were ranked by each performance measure and a multicriteria approach was used in selecting the most critical node. The ranked performance measures were subjected to five (5) case scenarios with different weight factors. Of the five cases studied node 80 ranked first for most critical node for the four case scenarios. While node 7 ranked first for one case scenario. This analysis makes it clear that node 80 is preferably the most critical node and most essential intersection which needs to be paid attention to during the 100-year flood disruption. It is worth stating that for each performance measure, a different node ranked first as most critical. It is also evident that the network is well connected and hence even after the deletion of nodes, the network wasn't redundant.

7.2 Conclusions

From the research conducted on this thesis, the findings contribute to the following conclusions:

- Easy evacuation of residents in flood hazard zones and similar deliberate attacks (earthquakes, typhoons) and human factors (war and COVID-19)
- This methodology is simple and convenient for large networks with constrained budget for the purpose of infrastructure planning, construction and maintenance.
- Identification and monitoring of nodes in a network which are most and least relevant in the system. The most relevant nodes can hence be developed into major roads (arterials and national highways)
- This also leads to the evaluation of the land based on the performance of the closest node.

APPENDIX A. NETWORK DATA

Table A.1 Data Collected on Kosciusko County Network

SOURCE	TARGET	DISTANCE (mi)	SPEED (mph)	TIME (hr)	TIME/(min)
1	2	2.06	45	0.05	2.75
1	16	0.98	45	0.02	1.31
2	3	1.56	45	0.03	2.07
2	13	2.02	45	0.04	2.69
3	4	0.39	45	0.01	0.52
3	13	2.42	30	0.08	4.83
4	5	0.85	45	0.02	1.13
4	12	0.97	45	0.02	1.29
5	6	1.50	45	0.03	2.01
5	11	0.98	45	0.02	1.30
6	7	0.40	50	0.01	0.48
7	9	0.99	50	0.02	1.19
7	8	0.99	50	0.02	1.19
8	10	0.99	50	0.02	1.19
8	37	1.23	50	0.02	1.48
9	10	0.99	50	0.02	1.19
11	12	0.70	45	0.02	0.93
13	14	0.18	45	0.00	0.23
14	15	0.46	45	0.01	0.62
14	23	1.36	45	0.03	1.81
15	16	2.74	25	0.11	6.58
16	17	0.50	45	0.01	0.67
16	18	0.50	45	0.01	0.66
17	22	0.93	45	0.02	1.24
18	19	1.44	45	0.03	1.91
19	49	1.52	50	0.03	1.83
22	23	1.49	45	0.03	1.99
23	24	0.63	45	0.01	0.84
24	25	1.73	45	0.04	2.31
25	26	0.50	45	0.01	0.67
26	27	0.76	45	0.02	1.01
27	28	0.50	45	0.01	0.66
28	29	0.50	45	0.01	0.67

Table A.1 Data Collected on Kosciusko County Network Contd.

28	48	0.25	45	0.01	0.33
29	30	0.49	45	0.01	0.66
30	31	0.31	45	0.01	0.41
31	44	0.83	45	0.02	1.11
33	41	1.00	45	0.02	1.33
33	34	0.95	45	0.02	1.27
34	35	0.48	20	0.02	1.45
35	36	1.06	20	0.05	3.19
36	37	0.50	20	0.03	1.50
37	38	2.21	20	0.11	6.62
38	39	0.84	20	0.04	2.52
39	40	2.06	20	0.10	6.17
41	42	0.35	45	0.01	0.47
42	95	1.04	35	0.03	1.79
42	43	0.62	45	0.01	0.83
43	44	0.19	45	0.00	0.25
44	46	0.77	45	0.02	1.03
45	52	1.40	45	0.03	1.86
46	47	0.50	45	0.01	0.66
47	48	0.50	45	0.01	0.67
48	49	1.97	45	0.04	2.63
49	50	1.26	50	0.03	1.51
50	51	0.50	50	0.01	0.60
51	52	0.99	45	0.02	1.32
52	53	0.48	45	0.01	0.64
53	54	0.24	45	0.01	0.32
53	54	1.50	35	0.04	2.58
55	90	0.24	35	0.01	0.41
55	90	0.26	50	0.01	0.31
55	91	0.24	30	0.01	0.49
56	90	1.77	35	0.05	3.04
56	57	1.80	35	0.05	3.08
57	58	0.75	35	0.02	1.28
58	59	0.24	35	0.01	0.42
59	60	0.49	35	0.01	0.84
60	61	0.94	35	0.03	1.62
61	62	0.74	35	0.02	1.27
62	66	0.69	35	0.02	1.18
62	84	0.50	35	0.01	0.85
63	66	0.49	35	0.01	0.84

Table A.1 Data Collected on Kosciusko County Network Contd.

63	64	0.59	35	0.02	1.01
64	65	1.02	35	0.03	1.75
65	66	0.74	35	0.02	1.27
65	67	0.50	35	0.01	0.85
67	68	0.99	35	0.03	1.70
68	69	0.96	35	0.03	1.65
69	70	0.99	35	0.03	1.70
67	70	0.74	35	0.02	1.27
70	71	0.98	35	0.03	1.67
71	72	0.25	55	0.00	0.27
72	73	1.18	55	0.02	1.29
73	75	0.97	55	0.02	1.06
74	75	1.17	55	0.02	1.27
75	76	1.49	55	0.03	1.63
76	77	1.00	55	0.02	1.09
77	80	1.00	55	0.02	1.09
79	80	0.25	55	0.00	0.27
78	79	1.24	35	0.04	2.13
69	78	0.44	35	0.01	0.76
80	114	0.50	35	0.01	0.86
81	82	0.48	35	0.01	0.82
81	115	0.75	35	0.02	1.28
82	83	0.47	35	0.01	0.80
82	117	0.49	35	0.01	0.83
83	84	0.99	35	0.03	1.70
85	86	0.52	50	0.01	0.62
85	116	0.78	35	0.02	1.33
86	87	0.95	50	0.02	1.14
86	119	0.49	50	0.01	0.59
87	88	0.71	50	0.01	0.85
88	89	1.29	50	0.03	1.54
89	90	0.24	50	0.00	0.29
91	92	0.25	30	0.01	0.51
92	93	1.00	30	0.03	2.00
93	94	1.03	30	0.03	2.05
93	104	0.59	50	0.01	0.71
94	95	1.01	30	0.03	2.01
94	97	0.50	35	0.01	0.86
95	96	0.47	35	0.01	0.81
96	97	0.50	35	0.01	0.85

Table A.1 Data Collected on Kosciusko County Network Contd

97	98	1.00	35	0.03	1.71
97	99	0.26	35	0.01	0.44
98	101	0.76	35	0.02	1.31
99	100	0.45	35	0.01	0.78
100	101	0.50	35	0.01	0.85
101	102	0.51	35	0.01	0.87
102	103	0.68	35	0.02	1.17
102	106	1.01	55	0.02	1.10
103	104	0.31	50	0.01	0.37
104	120	1.69	50	0.03	2.03
105	123	0.50	55	0.01	0.55
105	106	0.65	55	0.01	0.70
106	107	1.19	55	0.02	1.30
107	108	0.51	55	0.01	0.56
108	109	0.81	55	0.01	0.88
109	110	0.41	55	0.01	0.45
110	111	0.39	55	0.01	0.42
112	121	1.50	55	0.03	1.63
112	113	1.02	55	0.02	1.11
113	114	0.97	55	0.02	1.06
120	121	0.50	50	0.01	0.60
116	117	0.75	35	0.02	1.29
118	119	1.00	35	0.03	1.71
122	123	0.49	55	0.01	0.54

APPENDIX B. NODE RANKING BY PERFORMANCE MEASURES

Table B1. Ranked Nodes by Performance

DEGREE			CLOSENESS			EIGENVECTOR			BETWEENNESS		
Node	Value	Value fn	Node	Value	Value fn	Node	Value	Value fn	Node	Value	Value fn
16	4	100	11	1	100	48	1	100	5	44	100
2	3	75	9	1	100	114	0.971885	97	7	42	95
5	3	75	17	1	100	80	0.940578	94	6	40	91
7	3	75	49	1	100	10	0.827924	83	4	36	82
8	3	75	34	1	100	47	0.737002	74	71	32	73
28	3	75	39	1	100	46	0.714193	71	72	32	73
44	3	75	47	1	100	73	0.652515	65	8	31.5	72
42	3	75	53	1	100	72	0.651843	65	44	31	70
52	3	75	55	1	100	44	0.632605	63	70	30	68
62	3	75	58	1	100	75	0.609571	61	73	30	68
66	3	75	62	1	100	76	0.572722	57	75	30	68
65	3	75	63	1	100	71	0.572089	57	28	28	64
67	3	75	80	1	100	77	0.556352	56	3	26	59
69	3	75	83	1	100	50	0.448346	45	67	26	59
70	3	75	116	1	100	70	0.428435	43	29	25	57
75	3	75	88	1	100	40	0.423664	42	30	25	57
80	3	75	93	1	100	39	0.422941	42	37	24	55

Table B1. Ranked Nodes by Performance Contd.

82	3	75	98	1	100	38	0.420602	42	27	24	55
86	3	75	100	1	100	37	0.413962	41	31	23	52
1	2	50	103	1	100	9	0.397637	40	69	23	52
3	2	50	105	1	100	8	0.397637	40	76	23	52
4	2	50	110	1	100	31	0.397637	40	46	21	48
6	2	50	113	1	100	49	0.397341	40	16	18	41
11	2	50	120	1	100	7	0.363421	36	26	18	41
9	2	50	122	1	100	12	0.363421	36	38	18	41
10	2	50	82	0.75	75	30	0.363421	36	2	15	34
37	2	50	102	0.75	75	79	0.363421	36	65	15	34
15	2	50	112	0.75	75	6	0.303567	30	68	15	34
17	2	50	19	0.666667	67	11	0.303567	30	80	15	34
18	2	50	38	0.666667	67	29	0.303567	30	78	15	34
19	2	50	46	0.666667	67	78	0.303567	30	77	14	32
49	2	50	52	0.666667	67	22	0.29415	29	18	12	27
25	2	50	57	0.666667	67	19	0.29415	29	42	12	27
26	2	50	77	0.666667	67	84	0.249736	25	43	12	27
27	2	50	79	0.666667	67	101	0.228618	23	79	12	27
29	2	50	87	0.666667	67	5	0.218642	22	19	10	23
48	2	50	92	0.666667	67	28	0.218642	22	25	10	23
30	2	50	99	0.666667	67	69	0.218642	22	39	10	23
31	2	50	109	0.666667	67	89	0.218642	22	47	9	20
33	2	50	61	0.6	60	54	0.200375	20	15	7	16
41	2	50	86	0.571429	57	66	0.184204	18	41	7	16
34	2	50	81	0.555556	56	17	0.164253	16	49	6	14
38	2	50	37	0.5	50	18	0.164253	16	11	5	11
39	2	50	18	0.5	50	4	0.124868	12	17	4	9
43	2	50	44	0.5	50	27	0.124868	12	52	4	9
46	2	50	45	0.5	50	95	0.124868	12	62	4	9
47	2	50	51	0.5	50	43	0.124868	12	86	4	9

Table B1. Ranked Nodes by Performance Contd.

53	2	50	56	0.5	50	59	0.124868	12	87	4	9
57	2	50	76	0.5	50	68	0.124868	12	99	4	9
58	2	50	78	0.5	50	88	0.124868	12	9	3.5	8
61	2	50	97	0.5	50	100	0.124868	12	53	3	7
84	2	50	85	0.466667	47	117	0.098721	10	61	3	7
68	2	50	16	0.461538	46	104	0.098721	10	82	3	7
71	2	50	8	0.454545	45	53	0.088746	9	88	3	7
72	2	50	60	0.444444	44	16	0.059336	6	97	3	7
73	2	50	31	0.4	40	3	0.049361	5	100	3	7
76	2	50	43	0.4	40	13	0.049361	5	57	2	5
77	2	50	75	0.4	40	26	0.049361	5	58	2	5
79	2	50	94	0.4	40	35	0.049361	5	83	2	5
78	2	50	7	0.388889	39	42	0.049361	5	34	1	2
114	2	50	42	0.375	38	58	0.049361	5	116	1	2
81	2	50	15	0.35	35	62	0.049361	5	93	1	2
83	2	50	30	0.333333	33	67	0.049361	5	103	1	2
117	2	50	73	0.333333	33	83	0.049361	5	110	1	2
85	2	50	74	0.333333	33	87	0.049361	5	113	1	2
116	2	50	28	0.318182	32	119	0.049361	5	1	0	0
87	2	50	6	0.307692	31	99	0.049361	5	13	0	0
88	2	50	41	0.304348	30	111	0.049361	5	10	0	0
93	2	50	33	0.294118	29	52	0.01995	2	12	0	0
104	2	50	5	0.289474	29	106	0.01995	2	14	0	0
97	2	50	69	0.289474	29	123	0.01995	2	22	0	0
99	2	50	14	0.285714	29	121	0.01995	2	24	0	0
101	2	50	29	0.285714	29	2	0.009975	1	48	0	0
100	2	50	72	0.285714	29	15	0.009975	1	33	0	0
102	2	50	27	0.266667	27	25	0.009975	1	35	0	0
103	2	50	67	0.265306	27	41	0.009975	1	40	0	0
106	2	50	71	0.25	25	34	0.009975	1	95	0	0

Table B1. Ranked Nodes by Performance Contd.

105	2	50	4	0.24	24	90	0.009975	1	45	0	0
123	2	50	68	0.24	24	57	0.009975	1	50	0	0
110	2	50	65	0.234375	23	61	0.009975	1	51	0	0
112	2	50	26	0.230769	23	65	0.009975	1	54	0	0
121	2	50	70	0.222222	22	82	0.009975	1	55	0	0
113	2	50	3	0.206349	21	115	0.009975	1	90	0	0
13	1	25	25	0.204082	20	86	0.009975	1	56	0	0
12	1	25	1	0.201754	20	116	0.009975	1	59	0	0
14	1	25	64	0.2	20	93	0.009975	1	60	0	0
22	1	25	2	0.192308	19	97	0.009975	1	66	0	0
24	1	25	24	0.183333	18	103	0.009975	1	84	0	0
35	1	25	13	0	0	110	0.009975	1	63	0	0
40	1	25	10	0	0	113	0.009975	1	64	0	0
95	1	25	12	0	0	1	0	0	74	0	0
45	1	25	22	0	0	14	0	0	114	0	0
50	1	25	48	0	0	24	0	0	81	0	0
51	1	25	35	0	0	33	0	0	115	0	0
54	1	25	40	0	0	45	0	0	117	0	0
55	1	25	95	0	0	51	0	0	85	0	0
90	1	25	50	0	0	55	0	0	119	0	0
56	1	25	54	0	0	56	0	0	89	0	0
59	1	25	90	0	0	60	0	0	92	0	0
60	1	25	59	0	0	63	0	0	104	0	0
63	1	25	66	0	0	64	0	0	94	0	0
64	1	25	84	0	0	74	0	0	98	0	0
74	1	25	114	0	0	81	0	0	101	0	0
115	1	25	115	0	0	85	0	0	102	0	0
119	1	25	117	0	0	92	0	0	106	0	0
89	1	25	119	0	0	94	0	0	105	0	0
92	1	25	89	0	0	98	0	0	123	0	0

Table B1. Ranked Nodes by Performance Contd.

94	1	25	104	0	0	102	0	0	109	0	0
98	1	25	101	0	0	105	0	0	111	0	0
109	1	25	106	0	0	109	0	0	112	0	0
111	1	25	123	0	0	112	0	0	121	0	0
120	1	25	111	0	0	120	0	0	120	0	0
122	1	25	121	0	0	122	0	0	122	0	0

APPENDIX C. SENSITIVITY ANALYSIS NODE RANKING OF PERFORMANCE MEASURES

Table C.1 Sensitivity Analysis Case 1

Weight Factors	0.25	0.25	0.25	0.25	RESULTS	Rank
Node	Degree	Closeness	Eigenvector	Betweenness		
80	75	100	94	34	75.79	1
44	75	50	63	70	64.68	2
7	75	39	36	95	61.42	3
47	50	100	74	20	61.04	4
75	75	40	61	68	61.03	5
46	50	67	71	48	58.95	6
8	75	45	40	72	57.95	7
5	75	29	22	100	56.45	8
73	50	33	65	68	54.19	9
72	50	29	65	73	54.12	10
39	50	100	42	23	53.76	11
76	50	50	57	52	52.39	12
70	75	22	43	68	52.06	13
71	50	25	57	73	51.23	14
77	50	67	56	32	51.03	15
49	50	100	40	14	50.84	16
6	50	31	30	91	50.51	17
38	50	67	42	41	49.91	18
9	50	100	40	8	49.43	19
37	50	50	41	55	48.99	20
16	100	46	6	41	48.25	21
28	75	32	22	64	48.08	22
11	50	100	30	11	47.93	23
62	75	100	5	9	47.26	24
31	50	40	40	52	45.51	25
79	50	67	36	27	45.07	26
69	75	29	22	52	44.52	27
30	50	33	36	57	44.12	28
17	50	100	16	9	43.88	29
88	50	100	12	7	42.33	30
100	50	100	12	7	42.33	31

Table C.1 Sensitivity Analysis Case 1 Contd.

29	50	29	30	57	41.44	34
53	50	100	9	7	41.42	35
67	75	27	5	59	41.39	36
78	50	50	30	34	41.11	37
58	50	100	5	5	39.87	38
83	50	100	5	5	39.87	39
82	75	75	1	7	39.45	40
34	50	100	1	2	38.32	41
116	50	100	1	2	38.32	42
93	50	100	1	2	38.32	43
103	50	100	1	2	38.32	44
110	50	100	1	2	38.32	45
113	50	100	1	2	38.32	46
52	75	67	2	9	38.19	47
48	50	0	100	0	37.50	48
105	50	100	0	0	37.50	49
114	50	0	97	0	36.80	50
42	75	38	5	27	36.18	51
27	50	27	12	55	35.92	52
18	50	50	16	27	35.92	53
86	75	57	1	9	35.56	54
3	50	21	5	59	33.67	55
65	75	23	1	34	33.38	56
10	50	0	83	0	33.20	57
87	50	67	5	9	32.67	58
99	50	67	5	9	32.67	59
43	50	40	12	27	32.44	60
2	75	19	1	34	32.33	61
55	25	100	0	0	31.25	62
63	25	100	0	0	31.25	63
98	25	100	0	0	31.25	64
102	50	75	0	0	31.25	65
112	50	75	0	0	31.25	66
120	25	100	0	0	31.25	67
122	25	100	0	0	31.25	68
57	50	67	1	5	30.55	69
68	50	24	12	34	30.14	70
26	50	23	5	41	29.73	71

Table C.1 Sensitivity Analysis Case 1 Contd.

97	50	50	1	7	26.95	73
81	50	56	0	0	26.39	74
15	50	35	1	16	25.48	75
41	50	30	1	16	24.34	76
85	50	47	0	0	24.17	77
25	50	20	1	23	23.53	78
66	75	0	18	0	23.36	79
92	25	67	0	0	22.92	80
109	25	67	0	0	22.92	81
33	50	29	0	0	19.85	82
45	25	50	0	0	18.75	83
51	25	50	0	0	18.75	84
56	25	50	0	0	18.75	85
84	50	0	25	0	18.74	86
101	50	0	23	0	18.22	87
1	50	20	0	0	17.54	88
50	25	0	45	0	17.46	89
60	25	44	0	0	17.36	90
40	25	0	42	0	16.84	91
94	25	40	0	0	16.25	92
12	25	0	36	0	15.34	93
117	50	0	10	0	14.97	94
104	50	0	10	0	14.97	95
74	25	33	0	0	14.58	96
22	25	0	29	0	13.60	97
14	25	29	0	0	13.39	98
106	50	0	2	0	13.00	99
123	50	0	2	0	13.00	100
121	50	0	2	0	13.00	101
89	25	0	22	0	11.72	102
54	25	0	20	0	11.26	103
64	25	20	0	0	11.25	104
24	25	18	0	0	10.83	105
95	25	0	12	0	9.37	106
59	25	0	12	0	9.37	107
13	25	0	5	0	7.48	108
35	25	0	5	0	7.48	109
119	25	0	5	0	7.48	110

Table C.1 Sensitivity Analysis Case 1 Contd.

111	25	0	5	0	7.48	111
90	25	0	1	0	6.50	112
115	25	0	1	0	6.50	113

Table C.2 Sensitivity Analysis Case 2

Weight Factors	0.4	0.2	0.2	0.2	Total Points	Rank
Node	Degree	Closeness	Eigenvector	Betweenness		
80	75	100	94	34	75.63	1
44	75	50	63	70	66.74	2
7	75	39	36	95	64.14	3
75	75	40	61	68	63.83	4
8	75	45	40	72	61.36	5
5	75	29	22	100	60.16	6
47	50	100	74	20	58.83	7
16	100	46	6	41	58.60	8
46	50	67	71	48	57.16	9
70	75	22	43	68	56.65	10
28	75	32	22	64	53.46	11
73	50	33	65	68	53.35	12
72	50	29	65	73	53.30	13
39	50	100	42	23	53.00	14
62	75	100	5	9	52.81	15
76	50	50	57	52	51.91	16
71	50	25	57	73	50.99	17
77	50	67	56	32	50.82	18
49	50	100	40	14	50.67	19
69	75	29	22	52	50.62	20
6	50	31	30	91	50.41	21
38	50	67	42	41	49.93	22
9	50	100	40	8	49.54	23
37	50	50	41	55	49.19	24
11	50	100	30	11	48.34	25
67	75	27	5	59	48.11	26
82	75	75	1	7	46.56	27

Table C.2 Sensitivity Analysis Case 2 Contd.

31	50	40	40	52	46.41	28
79	50	67	36	27	46.06	29
52	75	67	2	9	45.55	30
30	50	33	36	57	45.30	31
17	50	100	16	9	45.10	32
42	75	38	5	27	43.94	33
88	50	100	12	7	43.86	34
100	50	100	12	7	43.86	35
19	50	67	29	23	43.76	36
4	50	24	12	82	43.66	37
86	75	57	1	9	43.45	38
29	50	29	30	57	43.15	39
53	50	100	9	7	43.14	40
78	50	50	30	34	42.89	41
58	50	100	5	5	41.90	42
83	50	100	5	5	41.90	43
65	75	23	1	34	41.71	44
2	75	19	1	34	40.86	45
34	50	100	1	2	40.65	46
116	50	100	1	2	40.65	47
93	50	100	1	2	40.65	48
103	50	100	1	2	40.65	49
110	50	100	1	2	40.65	50
113	50	100	1	2	40.65	51
48	50	0	100	0	40.00	52
105	50	100	0	0	40.00	53
114	50	0	97	0	39.44	54
27	50	27	12	55	38.74	55
18	50	50	16	27	38.74	56
3	50	21	5	59	36.93	57

Table C.2 Sensitivity Analysis Case 2 Contd.

10	50	0	83	0	36.56	58
87	50	67	5	9	36.14	59
99	50	67	5	9	36.14	60
43	50	40	12	27	35.95	61
102	50	75	0	0	35.00	62
112	50	75	0	0	35.00	63
57	50	67	1	5	34.44	64
68	50	24	12	34	34.12	65
26	50	23	5	41	33.78	66
66	75	0	18	0	33.68	67
61	50	60	1	7	33.56	68
97	50	50	1	7	31.56	69
81	50	56	0	0	31.11	70
15	50	35	1	16	30.38	71
55	25	100	0	0	30.00	72
63	25	100	0	0	30.00	73
98	25	100	0	0	30.00	74
120	25	100	0	0	30.00	75
122	25	100	0	0	30.00	76
41	50	30	1	16	29.47	77
85	50	47	0	0	29.33	78
25	50	20	1	23	28.83	79
33	50	29	0	0	25.88	80
84	50	0	25	0	24.99	81
101	50	0	23	0	24.57	82
1	50	20	0	0	24.04	83
92	25	67	0	0	23.33	84
109	25	67	0	0	23.33	85
117	50	0	10	0	21.97	86
104	50	0	10	0	21.97	87

Table C.2 Sensitivity Analysis Case 2 Contd.

106	50	0	2	0	20.40	88
123	50	0	2	0	20.40	89
121	50	0	2	0	20.40	90
45	25	50	0	0	20.00	91
51	25	50	0	0	20.00	92
56	25	50	0	0	20.00	93
50	25	0	45	0	18.97	94
60	25	44	0	0	18.89	95
40	25	0	42	0	18.47	96
94	25	40	0	0	18.00	97
12	25	0	36	0	17.27	98
74	25	33	0	0	16.67	99
22	25	0	29	0	15.88	100
14	25	29	0	0	15.71	101
89	25	0	22	0	14.37	102
54	25	0	20	0	14.01	103
64	25	20	0	0	14.00	104
24	25	18	0	0	13.67	105
95	25	0	12	0	12.50	106
59	25	0	12	0	12.50	107
13	25	0	5	0	10.99	108
35	25	0	5	0	10.99	109
119	25	0	5	0	10.99	110
111	25	0	5	0	10.99	111
90	25	0	1	0	10.20	112
115	25	0	1	0	10.20	113

Table C.3 Sensitivity Analysis Case 3

Weight Factors	0.2	0.4	0.2	0.2	Total Points	Rank
Node	Degree	Closeness	Eigenvector	Betweenness		
80	75	100	94	34	80.63	1
47	50	100	74	20	68.83	2
39	50	100	42	23	63.00	3
44	75	50	63	70	61.74	4
49	50	100	40	14	60.67	5
46	50	67	71	48	60.50	6
9	50	100	40	8	59.54	7
11	50	100	30	11	58.34	8
62	75	100	5	9	57.81	9
7	75	39	36	95	56.91	10
75	75	40	61	68	56.83	11
8	75	45	40	72	55.45	12
17	50	100	16	9	55.10	13
77	50	67	56	32	54.16	14
88	50	100	12	7	53.86	15
100	50	100	12	7	53.86	16
38	50	67	42	41	53.26	17
53	50	100	9	7	53.14	18
76	50	50	57	52	51.91	19
58	50	100	5	5	51.90	20
83	50	100	5	5	51.90	21
5	75	29	22	100	50.95	22
34	50	100	1	2	50.65	23
116	50	100	1	2	50.65	24
93	50	100	1	2	50.65	25
103	50	100	1	2	50.65	26
110	50	100	1	2	50.65	27

Table C.3 Sensitivity Analysis Case 3 Contd.

113	50	100	1	2	50.65	28
73	50	33	65	68	50.02	29
105	50	100	0	0	50.00	30
79	50	67	36	27	49.39	31
37	50	50	41	55	49.19	32
72	50	29	65	73	49.01	33
16	100	46	6	41	47.83	34
19	50	67	29	23	47.10	35
82	75	75	1	7	46.56	36
6	50	31	30	91	46.56	37
70	75	22	43	68	46.09	38
71	50	25	57	73	45.99	39
55	25	100	0	0	45.00	40
63	25	100	0	0	45.00	41
98	25	100	0	0	45.00	42
120	25	100	0	0	45.00	43
122	25	100	0	0	45.00	44
28	75	32	22	64	44.83	45
31	50	40	40	52	44.41	46
52	75	67	2	9	43.88	47
78	50	50	30	34	42.89	48
30	50	33	36	57	41.97	49
69	75	29	22	52	41.41	50
102	50	75	0	0	40.00	51
112	50	75	0	0	40.00	52
86	75	57	1	9	39.87	53
87	50	67	5	9	39.47	54
99	50	67	5	9	39.47	55
29	50	29	30	57	38.86	56
18	50	50	16	27	38.74	57

Table C.3 Sensitivity Analysis Case 3 Contd.

4	50	24	12	82	38.46	58
67	75	27	5	59	38.42	59
57	50	67	1	5	37.78	60
42	75	38	5	27	36.44	61
61	50	60	1	7	35.56	62
27	50	27	12	55	34.07	63
43	50	40	12	27	33.95	64
81	50	56	0	0	32.22	65
92	25	67	0	0	31.67	66
109	25	67	0	0	31.67	67
97	50	50	1	7	31.56	68
65	75	23	1	34	31.39	69
3	50	21	5	59	31.06	70
48	50	0	100	0	30.00	71
2	75	19	1	34	29.71	72
114	50	0	97	0	29.44	73
68	50	24	12	34	28.92	74
85	50	47	0	0	28.67	75
26	50	23	5	41	28.40	76
15	50	35	1	16	27.38	77
10	50	0	83	0	26.56	78
41	50	30	1	16	25.56	79
45	25	50	0	0	25.00	80
51	25	50	0	0	25.00	81
56	25	50	0	0	25.00	82
25	50	20	1	23	22.91	83
60	25	44	0	0	22.78	84
33	50	29	0	0	21.76	85
94	25	40	0	0	21.00	86
66	75	0	18	0	18.68	87

Table C.3 Sensitivity Analysis Case 3 Contd.

74	25	33	0	0	18.33	88
1	50	20	0	0	18.07	89
14	25	29	0	0	16.43	90
84	50	0	25	0	14.99	91
101	50	0	23	0	14.57	92
50	25	0	45	0	13.97	93
40	25	0	42	0	13.47	94
64	25	20	0	0	13.00	95
24	25	18	0	0	12.33	96
12	25	0	36	0	12.27	97
117	50	0	10	0	11.97	98
104	50	0	10	0	11.97	99
22	25	0	29	0	10.88	100
106	50	0	2	0	10.40	101
123	50	0	2	0	10.40	102
121	50	0	2	0	10.40	103
89	25	0	22	0	9.37	104
54	25	0	20	0	9.01	105
95	25	0	12	0	7.50	106
59	25	0	12	0	7.50	107
13	25	0	5	0	5.99	108
35	25	0	5	0	5.99	109
119	25	0	5	0	5.99	110
111	25	0	5	0	5.99	111
90	25	0	1	0	5.20	112
115	25	0	1	0	5.20	113

Table C.4 Sensitivity Analysis Case 4

Weight Factors	0.2	0.2	0.4	0.2	Total Points	Rank
Node	Degree	Closeness	Eigenvector	Betweenness		
80	75	100	94	34	79.44	1
44	75	50	63	70	64.40	2
47	50	100	74	20	63.57	3
46	50	67	71	48	61.45	4
75	75	40	61	68	61.02	5
7	75	39	36	95	56.41	6
73	50	33	65	68	56.40	7
72	50	29	65	73	56.33	8
8	75	45	40	72	54.31	9
76	50	50	57	52	53.36	10
71	50	25	57	73	52.43	11
77	50	67	56	32	51.95	12
39	50	100	42	23	51.46	13
70	75	22	43	68	50.22	14
48	50	0	100	0	50.00	15
5	75	29	22	100	49.54	16
114	50	0	97	0	48.88	17
49	50	100	40	14	48.62	18
38	50	67	42	41	48.34	19
9	50	100	40	8	47.50	20
37	50	50	41	55	47.47	21
6	50	31	30	91	46.48	22
11	50	100	30	11	44.42	23
31	50	40	40	52	44.36	24
79	50	67	36	27	43.32	25
10	50	0	83	0	43.12	26
28	75	32	22	64	42.84	27

Table C.4 Sensitivity Analysis Case 4 Contd.

30	50	33	36	57	42.57	28
69	75	29	22	52	39.99	29
16	100	46	6	41	39.79	30
19	50	67	29	23	39.64	31
29	50	29	30	57	39.22	32
78	50	50	30	34	38.96	33
62	75	100	5	9	38.79	34
17	50	100	16	9	38.39	35
88	50	100	12	7	36.36	36
100	50	100	12	7	36.36	37
4	50	24	12	82	36.16	38
53	50	100	9	7	34.91	39
67	75	27	5	59	34.10	40
58	50	100	5	5	32.88	41
83	50	100	5	5	32.88	42
18	50	50	16	27	32.02	43
82	75	75	1	7	31.76	44
27	50	27	12	55	31.24	45
52	75	67	2	9	30.95	46
34	50	100	1	2	30.85	47
116	50	100	1	2	30.85	48
93	50	100	1	2	30.85	49
103	50	100	1	2	30.85	50
110	50	100	1	2	30.85	51
113	50	100	1	2	30.85	52
105	50	100	0	0	30.00	53
42	75	38	5	27	29.93	54
86	75	57	1	9	28.65	55
43	50	40	12	27	28.45	56
3	50	21	5	59	27.92	57

Table C.4 Sensitivity Analysis Case 4 Contd.

87	50	67	5	9	27.13	58
99	50	67	5	9	27.13	59
65	75	23	1	34	26.90	60
68	50	24	12	34	26.61	61
2	75	19	1	34	26.06	62
55	25	100	0	0	25.00	63
63	25	100	0	0	25.00	64
98	25	100	0	0	25.00	65
102	50	75	0	0	25.00	66
112	50	75	0	0	25.00	67
120	25	100	0	0	25.00	68
122	25	100	0	0	25.00	69
26	50	23	5	41	24.77	70
57	50	67	1	5	24.64	71
61	50	60	1	7	23.76	72
50	25	0	45	0	22.93	73
66	75	0	18	0	22.37	74
40	25	0	42	0	21.95	75
97	50	50	1	7	21.76	76
81	50	56	0	0	21.11	77
15	50	35	1	16	20.58	78
84	50	0	25	0	19.99	79
41	50	30	1	16	19.67	80
12	25	0	36	0	19.54	81
85	50	47	0	0	19.33	82
101	50	0	23	0	19.14	83
25	50	20	1	23	19.03	84
92	25	67	0	0	18.33	85
109	25	67	0	0	18.33	86
22	25	0	29	0	16.77	87

Table C.4 Sensitivity Analysis Case 4 Contd.

33	50	29	0	0	15.88	88
45	25	50	0	0	15.00	89
51	25	50	0	0	15.00	90
56	25	50	0	0	15.00	91
1	50	20	0	0	14.04	92
117	50	0	10	0	13.95	93
104	50	0	10	0	13.95	94
60	25	44	0	0	13.89	95
89	25	0	22	0	13.75	96
54	25	0	20	0	13.02	97
94	25	40	0	0	13.00	98
74	25	33	0	0	11.67	99
106	50	0	2	0	10.80	100
123	50	0	2	0	10.80	101
121	50	0	2	0	10.80	102
14	25	29	0	0	10.71	103
95	25	0	12	0	9.99	104
59	25	0	12	0	9.99	105
64	25	20	0	0	9.00	106
24	25	18	0	0	8.67	107
13	25	0	5	0	6.97	108
35	25	0	5	0	6.97	109
119	25	0	5	0	6.97	110
111	25	0	5	0	6.97	111
90	25	0	1	0	5.40	112
115	25	0	1	0	5.40	113

Table C.5 Sensitivity Analysis Case 5

Weight Factors	0.2	0.2	0.2	0.4	Total Points	Rank
Node	Degree	Closeness	Eigenvector	Betweenness		
7	75	39	36	95	68.23	1
80	75	100	94	34	67.45	2
44	75	50	63	70	65.83	3
5	75	29	22	100	65.16	4
75	75	40	61	68	62.46	5
8	75	45	40	72	60.68	6
6	50	31	30	91	58.59	7
72	50	29	65	73	57.84	8
73	50	33	65	68	56.99	9
46	50	67	71	48	56.71	10
71	50	25	57	73	55.53	11
70	75	22	43	68	55.29	12
47	50	100	74	20	52.92	13
76	50	50	57	52	52.36	14
28	75	32	22	64	51.19	15
37	50	50	41	55	50.10	16
4	50	24	12	82	50.02	17
38	50	67	42	41	48.11	18
39	50	100	42	23	47.55	19
77	50	67	56	32	47.19	20
31	50	40	40	52	46.86	21
16	100	46	6	41	46.78	22
30	50	33	36	57	46.66	23
69	75	29	22	52	46.07	24
67	75	27	5	59	44.93	25
29	50	29	30	57	44.51	26
49	50	100	40	14	43.40	27

Table C.5 Sensitivity Analysis Case 5 Contd.

79	50	67	36	27	41.51	28
9	50	100	40	8	41.13	29
11	50	100	30	11	40.62	30
78	50	50	30	34	39.71	31
27	50	27	12	55	39.65	32
62	75	100	5	9	39.62	33
3	50	21	5	59	38.75	34
19	50	67	29	23	38.31	35
17	50	100	16	9	36.92	36
88	50	100	12	7	35.22	37
100	50	100	12	7	35.22	38
53	50	100	9	7	34.50	39
42	75	38	5	27	34.40	40
18	50	50	16	27	34.19	41
65	75	23	1	34	33.52	42
82	75	75	1	7	32.93	43
58	50	100	5	5	32.81	44
83	50	100	5	5	32.81	45
2	75	19	1	34	32.68	46
52	75	67	2	9	32.37	47
26	50	23	5	41	31.97	48
43	50	40	12	27	31.41	49
34	50	100	1	2	31.11	50
116	50	100	1	2	31.11	51
93	50	100	1	2	31.11	52
103	50	100	1	2	31.11	53
110	50	100	1	2	31.11	54
113	50	100	1	2	31.11	55
68	50	24	12	34	30.93	56
86	75	57	1	9	30.26	57

Table C.5 Sensitivity Analysis Case 5 Contd.

48	50	0	100	0	30.00	58
105	50	100	0	0	30.00	59
114	50	0	97	0	29.44	60
87	50	67	5	9	27.96	61
99	50	67	5	9	27.96	62
10	50	0	83	0	26.56	63
57	50	67	1	5	25.35	64
55	25	100	0	0	25.00	65
63	25	100	0	0	25.00	66
98	25	100	0	0	25.00	67
102	50	75	0	0	25.00	68
112	50	75	0	0	25.00	69
120	25	100	0	0	25.00	70
122	25	100	0	0	25.00	71
61	50	60	1	7	24.93	72
15	50	35	1	16	23.56	73
25	50	20	1	23	23.37	74
97	50	50	1	7	22.93	75
41	50	30	1	16	22.65	76
81	50	56	0	0	21.11	77
85	50	47	0	0	19.33	78
66	75	0	18	0	18.68	79
92	25	67	0	0	18.33	80
109	25	67	0	0	18.33	81
33	50	29	0	0	15.88	82
45	25	50	0	0	15.00	83
51	25	50	0	0	15.00	84
56	25	50	0	0	15.00	85
84	50	0	25	0	14.99	86
101	50	0	23	0	14.57	87

Table C.5 Sensitivity Analysis Case 5 Contd.

1	50	20	0	0	14.04	88
50	25	0	45	0	13.97	89
60	25	44	0	0	13.89	90
40	25	0	42	0	13.47	91
94	25	40	0	0	13.00	92
12	25	0	36	0	12.27	93
117	50	0	10	0	11.97	94
104	50	0	10	0	11.97	95
74	25	33	0	0	11.67	96
22	25	0	29	0	10.88	97
14	25	29	0	0	10.71	98
106	50	0	2	0	10.40	99
123	50	0	2	0	10.40	100
121	50	0	2	0	10.40	101
89	25	0	22	0	9.37	102
54	25	0	20	0	9.01	103
64	25	20	0	0	9.00	104
24	25	18	0	0	8.67	105
95	25	0	12	0	7.50	106
59	25	0	12	0	7.50	107
13	25	0	5	0	5.99	108
35	25	0	5	0	5.99	109
119	25	0	5	0	5.99	110
111	25	0	5	0	5.99	111
90	25	0	1	0	5.20	112
115	25	0	1	0	5.20	113

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