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FREIGHT ANALYSIS: EXTREME EVENTS AND VULNERABILITY

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Table of Contents

List of Tables

List of Figures

List of Papers

I. Shen, G., Aydin, S.G., 2012. Exploration and Visualization of National and Local Highway Freight Flows using Geographical Information Systems (GIS). *Journal of Geography and Regional Planning* 5 (10), pp. 263-286.

II. Aydin, S.G., Shen, G., Pulat, S.P., 2012. A Retro Analysis of I-40 Bridge Collapse on Freight Movement in the U.S. highway network Using GIS and Assignment Models. *International Journal of Transportation Science and Technology* 1 (4) pp. 379-397.

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Abstract

Freight transportation plays a vital role in our everyday lives as individuals, in business, and society as a whole. However, when compared to passenger transportation, the research focus on freight transportation is relatively young. This dissertation is a collection of published papers, aimed to build, develop and improve knowledge regarding freight transportation.

The dissertation specifically develops a framework to analyze freight transportation under extreme event conditions and investigates the vulnerability concept for the freight transportation system. First, we present the role of freight flow in the U.S. and other countries. Further, we decompose the freight transportation flow into four types: from, to, within, and through flows and analyze the flow at different geographic levels, such as at the state, regional, or Metropolitan Statistical Area (MSA) level. Using a linear regression model, we show that the decomposed freight flows can be linked to major socio-economic indicators, such as employment, revenue, income, and payroll. The regression model is illustrated at county level for the state of Oklahoma by disaggregating its MSAs, and at state level for the rest of the country. [Paper I].

The research shows that transportation system failures are, more often than not, fail due to extreme events such as man-made or natural disasters. As a result of the impacts from such disasters, the movement of freight changes. We analyze the I-40 Bridge collapse in Oklahoma of 2002, using two approaches. The first approach assigns the origin-destination freight flow to the network with the collapsed bridge removed. The second approach involves two successive assignments – first, by excluding the pre-hazard freight flow on the bridge and assigning the rest of the flow to the post disaster

network; and second, by assigning the freight flow on the bridge in pre-disaster conditions to the post-disaster-network. We show that the approaches represent two different objectives: (1) the immediate disaster response is planned or (2) the focus is on re-routing strategies. Once the objective is chosen, we can model the affect of an extreme event on freight movement. We additionally show that the models relying on the gravity-based spatial distance decay effects often overestimate the nearby freight flow changes while underestimating the further-out changes in the network [Paper II]. Furthermore, by developing a framework, we generalize the analysis of an extreme event impact on the freight flow and demonstrate that any extreme event can be analyzed by focusing on the "crippled" segment of the network while considering the effects of increased travel distances, time, cost, and, supply-demand changes following an extreme event. Alternative re-routing options and the impact of repair strategies are also discussed [Paper III].

In addition to the impact of the extreme events on freight flow, the dissertation investigates the reason behind the failures by defining and measuring the vulnerability of freight transportation systems. We define vulnerability based on the characteristics of freight systems; we specifically use multimodal freight systems to develop the concept and discuss risk and reliability. The characteristics of the multimodal freight system are inherently dynamic and also dependent on one another, as well as on other systems. We integrate not only the network (topological) but also temporal and geographic characteristics to model the freight transportation vulnerability [Paper IV]. Finally, we develop a methodology integrating graph theoretical measures and multi-attribute value theory. We illustrate the methodology with a case study of Hurricane Katrina of 2005, show how the network and freight flow attributes are used in identifying the vulnerability of freight.

Chapter 1: Introduction

Throughout history, goods movement, or freight transportation, has played an important role in societies' growth: history includes wars over not only the control of main transportation routes but also for the control of resources. Transportation routes generated income, increased opportunities, and provided grounds for exchange. Transportation enabled the spread of the written language from Mesopotamia to other communities, silk and spices from Asia, stretching from China, India, crossing over Anatolia, to Europe and to Americas.

The 21st century is not at all different: transportation plays a vital role in various dimensions of our lives and is essential to economic growth. Freight transportation increases the value of goods, extends the spatial boundaries of commodity and markets, and encourages competition. In chapter 2, we shortly review the role of freight and its significance. In chapter 3, we answer the questions of how freight transportation relates to socio-economic variables and how this information is useful in reflecting the economy. We present a short introduction to freight transportation and the freight flow studies in the literature. Then we focus on U.S. freight transportation and continue with a concise national overview of transported goods, as classified by the Standard Classification of Transport Goods (SCTG), and their movements on the highway network using a Geographical Information System (GIS) with the Freight Analysis Framework (FAF) data of years 2002, 2010, 2015, 2020, 2025, 2030, and 2035. In this section, a set of measures, mainly for analysis at the state level or Metropolitan Statistical Area (MSA) level freight flows for the U.S., is developed using the disaggregated freight flows (from, to, within, and through freight flows). We use these measures to classify a state or an MSA as a production, attraction, or a through state or MSA. In general, we can say that an attraction state is less self-sufficient than a production state. Comparisons of states based on these measures are presented. We show that some production states become less productive during the study interval, while the total freight for the U.S. increases. Similarly, within freight flow of each state increases in the course of study interval. Next, by developing a linear regression model, we establish a link between the freight flow and the socio-economic variables. We show that the regression models are statistically significant, particularly for attraction (to flow) and within flows that have R-square values between 87.8% and 89.9%. In contrast, through flows are not significantly explained by the same set of variables.

After establishing the relationship between socio-economic variables and the freight flow under normal conditions, in chapter 4 we focus on how all-commodity freight flows change in cases of extreme events with the man-made disaster scenario of the I-40 Bridge collapse in Oklahoma, 2002. This chapter is adopted from Aydin, 2009, and presented here to establish the background and continuum of topics. For the I-40 Bridge collapse scenario we use the county level detail for the state of Oklahoma utilizing the data and U.S. roadway network provided by the FAF, $FAF^{2.2}$ database. The freight flow changes due to the bridge collapse are analyzed using two different assignment approaches. The first approach assigns the origin-destination freight flow to the network with the collapsed bridge removed. The second involves two successive assignments – first, by excluding the pre-hazard freight flow on the bridge and assigning the rest of the flow to the post-disaster network, and second, by assigning the freight flow on the bridge in pre-disaster conditions to the post-disaster-network. We show that the approaches represent different conditions, i.e. different time points of the disaster conditions, which can be chosen to match the purpose of the decision makers to provide insights as to the freight flow status, re-routing, and possibly repair strategies. We also show that a bridge collapse does not only impact the freight flows on nearby highway network links, but also affects flows on links further away from the bridge. This result casts doubt on the conventional models relying on the gravity-based spatial distance decay effects, which often overestimate the nearby while underestimating the further-out freight flow changes in the network.

Moreover, a unified framework is developed to simulate, analyze, and compare the impact of any extreme event. The framework is discussed in chapter 5. We make use of common flow-based and flow-independent measures, which enable the comparison of different scenarios. We illustrate the framework with natural and man-made disasters: the Northridge Earthquake of 1994, the I-40 Bridge collapse of 2002 and the Hurricane Katrina of 2005. Based on the change in freight flow on the network, we compare the disasters, finding that the more severe the disaster, the higher the change. The analyses show that the effect of Hurricane Katrina on freight flow was more severe than the effect of Northridge earthquake on freight flow, which was more severe than the effect of I-40 Bridge collapse on freight flow. The freight flow change for the Functional Classification (FCLASS) of road classification, the Northridge earthquake and I-40 bridge collapse disasters were similar; in both cases the disrupted freight flow shifted more to major and minor arterials as compared to the interstates. In the case of Hurricane Katrina the freight flow specifically decreased on interstates.

In addition to the analysis of the extreme event impacts on freight flows, in chapter 6 we investigate the definition of vulnerability of freight transportation systems: what causes the transportation systems to fail and how we can quantify this vulnerability. The characteristics of the freight system are inherently dynamic and also dependent upon smaller systems such as the actual network and the fleet services, as well as upon other systems, such as the transportation system as a whole. We discuss reliability, risk and vulnerability in the context of multimodal freight transportation systems. By linking the topological, temporal, and geographic characteristics of the transportation system, we define vulnerability as the change experienced in the facets of the freight transportation system due to the extreme event. The concepts are illustrated using the impact of Hurricane Katrina' on the freight flow within the disaster region and the U.S. as a whole. We show that the vulnerability of the freight transportation is the highest in Louisiana (LA), followed by Mississippi (MS), and the U.S. at the national level. Similarly, the vulnerability of each route can be calculated by quantifying the change in the system characteristics. Lastly in Chapter 7, we summarize the conclusions and direct attention to future research questions.

Chapter 2: Role of Freight Transportation and Background

The freight transportation system, and transportation systems in general, contribute to the economy. In the U.S., the transportation industry employed more than 20 million people with transportation-related goods and services sector in 2002, which accounted for 10% of the total employment and represented 10% of the Gross Domestic Product (GDP) [USDOT BTS, 2004]. In EU-27, the transportation industry directly employed 10 million people in 2009, which is 4.5% of the total employment and represented 4.6% of the GDP [EuroStat, 2011].

The global economy relies heavily on the efficient freight transportation systems. Due to the extensive globalization, freight movement has become essential to economic and social vitality as it provides necessities that are no longer produced locally for a community. The U.S. transportation system moved nearly 3.5 trillion ton-miles (5.6 trillion ton-km) of freight in the year 2007 [USDOT BTS, 2009], China 6.85 billion ton-miles (11 billion ton-km) in 2008, and in 2009 European Union countries (EU-27) 2.3 trillion ton-miles (3.6 trillion ton-km) and Russia 4.6 billion ton-miles (7.4 billion ton-km) [EuroStat, 2011]. As we become more globally connected, businesses require well-connected and efficient transportation systems to lower product and service costs.

Vast network systems are developed to satisfy the demand. For instance, the U.S. has the world's most extensive freight transportation network of public-use paved roads, railways, waterways, pipelines, and airports [USDOT, 2010]. In addition, there are more roadway kilometers per person than in Japan, United Kingdom, or France, due to low population density and vast geography. The U.S. also has a higher transportation intensity (21), compared to other leading countries such as Japan (9.4), United Kingdom

(6.5), and France (14.9) [EuroStat, 2011]. Here, the intensity is defined as a ratio of the extent of the physical transportation system to the geographical area it covers to the population size. Higher transportation intensity indicates a relative concentration of the infrastructure that is available for use by the population [USDOT, 2010]. Therefore, a higher intensity results in a higher level of freight activity. Research also shows that freight movement varies in a similar fashion as GDP; the freight movement increases when the GDP increases and decreases when the GDP decreases [USDOT BTS, 2009]. The freight data, therefore, provides valuable information about regions.

Freight data plays an important role in transportation decisions, such as infrastructure, investment, safety, and security. The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 was a major step in 'the renewal of [U.S.] our surface transportation programs to address the changing needs for America's will to create jobs, reduce congestion, and rebuild our infrastructure' [Skinner,1991]. The purpose of ISTEA 1991 was to 'develop a National Intermodal Transportation System that is economically efficient, environmentally sound, provides the foundation for the Nation to compete in the global economy and will move people and goods in an energy efficient manner' [Skinner, 1991]. In comply with ISTEA 1991, Metropolitan Planning Organizations (MPOs) and all other regional and local planning agencies include freight transportation issues in state and metropolitan transportation plans [Siwek, 1996]. A National Commission on Intermodal Transportation was also established 'to study the status of intermodal standardization, intermodal impacts on public works infrastructure, legal impediments to efficient intermodal transportation, financial issues, new technologies, problems in documenting intermodal transfers of freight, research and development needs, and the relationship of intermodal transportation to productivity' [ISTEA,1991]. The Transportation Equity Act for the 21st Century (TEA-21) and the Safe, Accountable, Flexible, Efficient Transportation Act (SAFETEA-LU) of 2005 both continued to support ISTEA [FHWA, 2005; 2011].

Several states prepared localized freight movement studies and developed statewide freight flow models. For instance, the Florida model is capable of identifying and measuring truck activity on highways, the Iowa multimodal and multicommodity freight movement model simulates the impact of transportation and non-transportation related changes on freight flow and utilizes the model in making decisions such as industry locations and public policy [Souleyrette et al., 1996]. And, the Ohio freight model uses regional, industry, and commodity models to forecast freight movement patterns by commodity by mode for freight corridors, whereas the Wisconsin model focuses on major manufacturing commodities and model state-level heavy truck movements. Another example is the Oklahoma model, which estimates freight flows for all states, and specifically for all counties in Oklahoma by commodity and by mode [Pulat et al., 2003]. The Oklahoma model was extended to an MSA-level 5-county regional freight study by Shen and Pulat [2006]. The Oklahoma model is different than existing freight movement models with its unique code mapping between the industry and commodity data (further details available at Ojha, 2008).

We generally plan for normal conditions, and rarely for extreme events, which disrupt the usual flow of life, for instance by damaging the transportation network. Such damages cause the transportation network disruptions, which result in social and economic losses: congestion, closed roads, restricted lanes, trip cancellations, re-routing, or delays.

These cause the passenger and freight movement to deviate from the usual routines, for example, by eliminating the trip completely, changing the route (re-routing), or by costing higher on the same path. Understanding the behavior of freight before, during and after extreme events is of utmost importance for mitigation and restoration.

For this purpose, we first analyze the freight data, using $FAF^{2.2}$, relating the social and economic variables to freight flow, and then analyze the effects of different extreme events on freight flow with the previously mentioned two traffic assignment approaches and the unified framework we develop. Investigating how the damage can be quantified, we use multimodal transportation systems to define vulnerability of freight and discuss risk and reliability within the concept of freight movement. Further background research is provided in each chapter.

Chapter 3: Freight Data Analysis: Overview

Societies rely on several systems, such as the utility systems, to function: eat, live, transport, work, communicate etc. Freight movement is one such system, which supports our life quality. Therefore understanding the freight volume within the U.S. will not only provide us the necessary insight in regard to the scale of the system but also provide the tools to shape the future of freight movement, such as decision-making on policies, maintenance, cost shares of toll roads, emergency management, and mitigation efforts.

In this chapter, we present an overview of the research published in Shen and Aydin [2012]. Here, improving the models developed by Chin et al. [1998, 2001] and Shen and Pulat [2006], the freight flow is investigated in detail with the disaggregated flow structure (from a state, to a state, within a state, and through a state); and by using flow parameters, all states are also compared and ranked . A linear regression model for freight transportation is developed to link the freight flow to the economic factors at the state level for the year 2002. This chapter aims to illustrate how freight flow analysis can guide decision makers, transportation planners, and researchers in making better decisions by utilizing the freight transportation data available in publicly accessible databases.

3.1 Data Sources and Tools

Freight analysis requires processing, linking and manipulating of various databases, as well as creation, maintenance, support and use of transportation networks and GIS software. In this section, we highlight commonly used terminology, resources and software tools such as the FAF, SCTG, North American Industry Classification System (NAICS), and TransCAD.

Standard Classification of Transported Goods (SCTG)

SCTG consists of a blend of transportation characteristics, commodity similarities and industry-of-origin considerations, designed to create statistically significant categories. The SCTG is designed to provide commodity groupings that better reflect goods transported by all modes. The structure of the SCTG is hierarchical, consisting of four levels that contain groupings based on the Harmonized Commodity Description and Coding System (HS) or Standard Classification of Goods (SCG) "building blocks." The SCTG follows the classification principles that each level covers the universe of transported goods and that each category in each level is mutually exclusive. The number of categories in each level ranges from a minimum of 42 to a maximum of 512.

The North American Industry Classification System (NAICS)

NAICS is the standard used by the Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing and publishing statistical data related to U.S. business economy.

Freight Flow Data

The freight flow data are commodity flows at a specific geographical level, e.g. states or MSAs. Some of the publicly available freight databases are the FAF, Commodity Flow Survey developed by the Census Bureau and the Bureau of Transportation Statistics (BTS) of U.S. Department Of Transportation (DOT), Geo Freight by BTS and Federal Highway Administration (FHWA), Rail Waybill Data by Federal Railroad

Administration. These freight databases are integrated and linked to the highway transportation network databases. The FAF differentiates between various commodities by using the SCTG that creates statistically significant transportation categories and covers the universe of transported goods. Within each of the four levels of the SCTG, each category at that particular level is mutually exclusive (for more see SCTG Codes).

Freight Analysis Framework (FAF)

FAF provides one of the most comprehensive freight data sources; integrates various sources, such as the Commodity Flow Survey (CFS) and other surveys. FAF provides freight movement data by regions (e.g. state, MSAs), by commodity, and by mode in terms of both tonnage and dollar values. Last release is FAF^{3} version, which provides estimates for 2007 and forecasts through 2040. Previous versions are FAF^{1} and FAF$^{2.2}$; FAF$^{2.2}$ provides estimates for 2002 and forecasts through 2035.

This study utilizes the FAF$^{2.2}$ database, which has a collection of commodity flows (given in tons and in dollar values) among the states, major MSAs, and the international gateways for year 2002 and the estimated flows for every five years from 2010 to 2035.

The U.S. Highway Network

The U.S. highway network is available from several databases: the National Transportation Atlas Database (NTAD), National Highway Planning Network (NHPN) databases, the Census Bureau's Tiger database, the GIS database provided by Environmental Systems Research Institute, Inc. (ESRI), and the FAF databases. The main difference between these sources can be listed as the level of detail and the attribute information provided with the network.

For the purposes of this study, the U.S. highway network from FAF, 2.2 version, is utilized because of its comprehensive quality as well as the freight data availability from the same source. This highway network consists of 46,380 miles of Interstate highways, 162,000 miles of National Highway System (NHS) (excluding Interstates), 35,000 miles of other national network roads and 2,125 miles of urban streets and rural minor arterials. These roads are available in TransCAD and ESRI formats, TransCAD format has 170,772 links of various lengths. In addition, this highway network includes various transportation attributes, such as the network capacity, volume, free flow speed and travel time, which can be used for the capacity-constrained assignment.

TransCAD

TransCAD is a GIS based software package with built-in assignment algorithms, such as All-or-Nothing (AON) and User Equilibrium (UE), which was designed with a focus on transportation applications. It is a widely used transportation analysis and modeling tool [TransCAD, 2005]. TransCAD is used for traffic assignment and data visualization in this study (refer to Ojha, 2008 and TransCAD, 2005 for more on traffic assignments).

Traffic Assignment Models

The most widely used flow assignment models in transportation planning are AON, UE, System Optimum (SO), and Stochastic User Equilibrium (SUE) [Sheffi, 1985]. In this study, we utilize the AON and UE assignment models.

The AON algorithm is based on the assumption that users make route choices based on the minimum distance from an origin to a destination. This is the most basic assignment model and the simplest to execute. The AON model doesn't consider link capacity or travel time; it is categorized as an un-capacitated assignment model that assumes travel time is fixed and independent of the link capacity. It uses the shortest-path algorithm in assigning the flow to the shortest path for each origin and destination pair. Even though the AON model is criticized as not representing actual user preferences because of excluding the capacity factor, the AON model assists, for instance, transportation planners in determining the required traffic capacity to be supplied, in decision of traffic capacity for new roads, or to be removed from a link to meet the desired service level (i.e. partially or completely closing a road for maintenance purposes), which is one of the purposes of transportation planning. It is also useful for emergency planning in simulating the traffic conditions right after an extreme event, when the traffic volumes are low or nonexistent due to the event.

The UE is a non-linear capacitated deterministic equilibrium flow algorithm, which is based on the assumption that users have perfect knowledge of the travel costs on a network and choose routes to minimize individual user costs [Sheffi, 1985], (i.e. travel time or cost per person). It uses the link capacity constraints and requires an iterative procedure between flow assignments and loaded travel times. The UE model is:

$$\text{Min } \sum_l \int_0^{v_l} S_l(x)dx \tag{3.1}$$

$$\text{s.t. } v_l = \sum_i \sum_j \sum_r \delta_{ij}^{lr} x_{ij}^r \tag{3.2}$$

$$\sum_r x_{ij}^r = F_{ij} \tag{3.3}$$

$$v_l \leq C_l \tag{3.4}$$

$$v_l \geq 0, x_{ij}^r \geq 0 \tag{3.5}$$

where parameter $\delta_{ij}^{lr} = 0{,}1$ and is 1 if link l is on path r from i to j; zero otherwise. $S_l(x)$ is a function of flow x_{ij}^r on link l from i to j on path r, F_{ij} is the total freight flow from origin i to destination j; v_l is the total flow volume on link l, and C_l the capacity of link l. The objective function is to minimize the total travel cost on links. Constraint (3.2) specifies that flow volume on link l is the sum of all flows from all paths and all origins and destinations using that link. Constraint (3.3) requires that each Origin-Destination (OD) flow must be assigned. Constraint (3.4) specifies link capacity. Constraint (3.5) ensures non-negativity for link or path volume. The UE and AON assignment procedures are readily available in TransCAD.

3.2 Methodology

In this section, we disaggregate the freight flow data into four categories based on the origin and destination information, then compare freight flow compositions, analyze the differences of the disaggregated freight flows for each state, and next compare and rank the states in each category. We additionally disaggregate the freight flow for the state of Oklahoma down to the county level. Lastly, we explore the relationship between the freight flow and the economic components of the transportation industry by utilizing the 2002 freight flow data, both at the state level and at the county level for Oklahoma.

Freight Data Preparation

The $FAF^{2.2}$ database provides the freight data by tonnage for OD pairs, at MSA level. Oklahoma freight data is provided for two MSAs – Oklahoma City area (OK Oklah) and Tulsa (OK Tulsa) – and the remainder of the state (OK rem). The Oklahoma and Tulsa MSAs each consist of 8 counties with the other 61 counties represented as the reminder. A methodology is developed to split this regional level freight data into county level data: the freight production data, the employment data by commodity and the freight attraction data [Ojha, 2008]. The population by county is used to split the freight flow data provided by FAF. The reasoning behind the use of employment and population data is that the production of each commodity is directly related to the number of employees working to produce that commodity and the attraction of any commodity is directly related to the population of the area [Shen et al., 2009].

The U.S. Census Bureau provides the employment data at the County Business Pattern (CBP) database for each industry at the county level by NAICS codes, whereas the freight movement data is provided by the STCG codes (by FAF). Therefore, a code mapping methodology, which establishes a bridge between SCTG and NAICS codes is needed, so that the employment involved in producing each of the commodities is determined [Ojha, 2008]. Population data for year 2002 was obtained from CBP database. Using the employment and population data for each county, state/MSA level production and attraction data can be disaggregated to the county level. Production flow, P_o^i the amount of flow produced (the supply) by county *i* in state *O*, can be defined using the following formula:

$$P_o^i = P_o * {EMP_o^i}\Big/{\sum_{i=1}^{n} EMP_o^i}$$

where *i* is the county that belongs to state o (e.g., Oklahoma), P_O is the total production of the state o, *n* is the total number of counties in the state (e.g. *n* = 77 counties in Oklahoma), and $\mathrm{EMP_R^i}$ is the employment of the county *i*, in state o. Attraction flow, A_o^i the amount of flow attracted (the demand), to county *i* in state *O*, can be defined using the following formula:

$$A_o^i = A_o * {POP_o^i}\Big/{\sum_{i=1}^{n} POP_o^i}$$

where *i* is the county that belongs to state o, A_o is the attraction of the state, *n* is the total number of counties in the state, and POP_o^i is the population of the county *i* in state o.

The commonly available freight data, such as the data provided by FAF, is in tonnage and in dollar values. Although the freight unit is not important for the AON assignment, the UE assignment needs the freight unit to match the capacity information for the network, in this case it is the number of trucks. The Freight Analysis Framework Highway Capacity Analysis Methodology Report [Cambridge Systems, 2009] provides a chart of average payload factors by Standard Transportation Commodity Code (STCC) [USDOT BTS, 2007] and truck types (single unit truck, semi-trailer, double trailer, and triples). The conversion of STCC and SCTG was prepared by DRI-WEFA [2002] "Commodity Flow Forecast Update Report." Average payload factors were used to convert the total freight tonnage to determine the number of trucks between each OD pairs, which was used for assignments [Ojha, 2008].

Freight Flow Composition

Freight flow can be disaggregated into four categories based on the origin and destination of the flow: from, to, within, and through flow:

- 'From freight flow' is the total freight transported from a region, e.g. from Oklahoma flow is the total number of freight transported to all other states (domestic freight only). From freight flow is also referred to as the freight production of a region.
- 'To freight flow' is the total freight flow that is received by a region, e.g. to Oklahoma flow' is the freight flow transported to Oklahoma from all other states. To freight flow is also referred to as the freight attraction of a region.
- 'Within freight flow' is the amount of freight flow that is transported within the same region; e.g. within Oklahoma flow is the total freight flow that is

transported within the regions of Oklahoma, between the Oklahoma MSAs or counties of Oklahoma.

- 'Through freight flow' of a region neither originates from nor is delivered to the respective region; it is the freight flow that passes through the region. For instance, Oklahoma through flow is the total freight flow that passes through Oklahoma when neither the origin nor the destination of the freight flow is Oklahoma.

We can formulate the freight flow categories as follows: let X_{mt}^{od} be the freight flow from state o to state d for commodity m in year t:

I. 'from freight flow', FF_t^o, of state o in year t:

$$FF_t^o = \sum_{dm} X_{mt}^{od} \tag{3.6}$$

II. 'to freight flow', TF_t^o, of state o in year t:

$$TF_t^o = \sum_{dm} X_{mt}^{do} \tag{3.7}$$

III. 'within freight flow', WIF_t^o of state o in year t:

$$WIF_t^o = \sum_{o=dm} X_{mt}^{od} \text{ , where } o = d \tag{3.8}$$

IV. 'through freight flow', THF_t^o of state o in year t:

$$THF_t^o = \text{assigned} \left(\sum_{jm} X_{mt}^{ij}\, \delta_{mt}^{ioj} + \sum_{im} X_{mt}^{ij}\, \delta_{mt}^{ioj}\right) \tag{3.9}$$

where through freight flow is represented as the total assigned freight flow between states i and j, and the shortest path between these two states passes through the state o. The through freight flow calculation is based on the AON assignment, where $i \neq j \neq o$ and $\delta_{mt}^{ioj} = 1$ if state o is on the shortest path linking states i and j, else, $\delta_{mt}^{ioj} = 0$.

Freight Flow Measures

We define 'producing state' and 'attracting state' to classify states based on the freight supply and demand of the respective region. Similar to the supply-demand balance, if a region is consuming (or attracting) more than it is producing, then this region is dependent on other regions to satisfy the regional demand. 'From flow production' (FFP_t^o) is the ratio of region o's freight production in year t to the sum of its total freight production and attraction in year t. FFP_t^o is an indicator of a state's dependency on the commodities transported from other states. We can formulate it as follows:

$$FFP_t^o = FF_t^o / (FF_t^o + TF_t^o) \tag{3.10}$$

It can be easily seen that 'to flow production' (TFP_t^o) is the complement of FFP_t^o and can be formulated at follows:

$$TFP_t^o = 1 - FFP_t^o \tag{3.11}$$

Similarly, measures can be defined for 'within flow production' ($WIFP_t^o$) to show a region's self-sufficiency, and 'through flow production' ($THFP_t^o$) to show the role of the state's network in freight movement of other regions.

$$WIFP_t^o = WIF_t^o / (WIF_t^o + TF_t^o) \tag{3.12}$$

$$THFP_t^o = TH_t^o / (FF_t^o + TF_t^o + THF_t^o) \tag{3.13}$$

Regression Linkage of Freight Flows and Economic Factors

Freight transportation is the result of production and demand being spatially separated; and because of the need for freight transportation, we have infrastructure, fleets, employees to serve this need. However, how do we link these factors? For this purpose, we develop a linear regression model of employment (EMP_t^o), number of establishments (EST_t^o), revenue (REV_t^o), and payroll (PAY_t^o) of the transportation sector

(NAICS codes 48-49), and the total from, to, within and through freight flows of the state o in year t. For example, we can explain employment, the dependent variable with the following independent variables: from (production), within freight flow, to (attraction) freight flow, and through freight flow. Each independent variable can be represented as:

$$EMP_t^o = a_0 + a_1 FF_t^o + a_2 TF_t^o + a_3 WIF_t^o + a_4 THF_t^o + e_{EMP} \tag{3.14}$$

$$EST_t^o = b_0 + b_1 FF_t^o + b_2 TF_t^o + b_3 WIF_t^o + b_4 THF_t^o + e_{EST} \tag{3.15}$$

$$REV_t^o = c_0 + c_1 FF_t^o + c_2 TF_t^o + c_3 WIF_t^o + c_4 THF_t^o + e_{REV} \tag{3.16}$$

$$PAY_t^o = d_0 + d_1 FF_t^o + d_2 TF_t^o + d_3 WIF_t^o + d_4 THF_t^o + e_{PAY} \tag{3.17}$$

where $e_{EMP}, e_{EST}, e_{REV}, e_{PAY}$ are the error terms for the regressions.

In the next section, we use the freight data and the measures to analyze the measures we defined in this section.

3.3 Freight Data Analysis at the National Level

The freight data and the roadway network are retrieved from the FAF$^{2.2}$ database. The data are summarized by state for all commodities in thousands of tons for years 2002 to 2035, in five-year increments. Freight flow is assigned with the use of the AON assignment model. Through freight flow is determined for every origin-destination pair by determining the total freight flows utilizing other state's roadway network. The freight data is analyzed from two perspectives: geographically at the national and local levels, and freight composition by from, to, within and through freight information, which provide a unique perspective of the economy.

From Flow (Freight Production)

The total freight production increases between 2002 and 2035 at the national level, from 2,505 ktons to 5,764 ktons. The top 10 states are shown in Table 3.1. Geographically 7 of the 10 states are in the north and north-east of U.S., and the rest are in the south (TX, GA, MO). However, the total share of freight production of these top 10 states decreases from 44.19% to 37.34% between 2002 and 2035, suggesting some other states experience a greater increase in freight production.

Table 3.1: Top 10 freight production states (thousand tons or ktons).

State	2002	2010	2015	2020	2025	2030	2035
IL	207	222	235	253	281	312	345
OH	138	181	191	199	210	226	243
PA	116	113	116	122	131	143	158
IN	102	131	152	175	209	246	291
NJ	100	114	130	149	174	206	244
TX	97	118	136	162	193	229	263
GA	89	111	121	136	157	185	220
MO	88	107	121	140	162	188	218
WI	87	60	60	62	66	70	77
NY	83	76	77	77	79	87	93
Top 10 Sum	1,107	1,233	1,339	1,475	1,662	1,892	2,152
Total	2,505	2,960	3,288	3,706	4,263	4,961	5,764
Top 10/National	44.19%	41.66%	40.72%	39.80%	38.99%	38.14%	37.34%

A closer look at the top 10 shows that the top 8 have a steady growth rate whereas the last two, WI and NY, experience fluctuations. It can also be seen that IN, TX, and NJ have the highest freight production quantities.The total production freight flow percentage change is 12% in NY, and highest change is 365% in KY, whereas the national average is 137%. Following KY, ID grows 359%, MI 346%, and OR 308%.

Top and bottom changes in freight production by year are given in Table 3.2. The states of IL, OH, IN, TN, and MO rank in percentage increase of freight production at the top 5 for the year 2002, but future estimates show a change in the ranking, where KY rises in the list to the 3rd spot by year 2035.

Table 3.2: Top and bottom 10 change in freight production, 2002-2035.

State	2002	2010	2015	2020	2025	2030	2035	2035 Rank
IL	8.26%	7.52%	7.15%	6.83%	6.60%	6.29%	5.98%	1
MI	2.96%	3.12%	3.62%	4.15%	4.74%	5.20%	5.74%	12
KY	2.79%	3.30%	3.65%	4.09%	4.65%	5.15%	5.63%	14
IN	4.05%	4.42%	4.61%	4.74%	4.91%	4.97%	5.06%	4
MO	3.89%	4.00%	4.14%	4.38%	4.53%	4.63%	4.56%	6
CA	2.34%	2.88%	3.13%	3.38%	3.64%	3.95%	4.34%	18
TN	4.00%	3.86%	3.95%	4.02%	4.07%	4.15%	4.24%	5
OH	5.52%	6.10%	5.81%	5.36%	4.94%	4.56%	4.22%	2
TX	3.57%	3.75%	3.68%	3.67%	3.68%	3.73%	3.82%	7
MD	2.41%	2.82%	2.91%	3.16%	3.39%	3.68%	3.80%	17
Top 10 Sum	39.78%	41.77%	42.65%	43.78%	45.14%	46.31%	47.39%	
ME	0.59%	0.51%	0.52%	0.56%	0.57%	0.58%	0.57%	42
NM	0.36%	0.42%	0.44%	0.46%	0.48%	0.49%	0.52%	46
WY	0.56%	0.51%	0.51%	0.51%	0.51%	0.51%	0.52%	44
NV	0.56%	0.53%	0.52%	0.51%	0.51%	0.51%	0.51%	43
RI	0.47%	0.43%	0.49%	0.51%	0.52%	0.49%	0.48%	45
WA	1.00%	0.88%	0.78%	0.68%	0.58%	0.49%	0.42%	34
VT	0.33%	0.35%	0.34%	0.34%	0.35%	0.35%	0.37%	47
MT	0.27%	0.25%	0.25%	0.25%	0.25%	0.25%	0.25%	48
DC	0.09%	0.07%	0.06%	0.06%	0.05%	0.05%	0.05%	49
AK	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	50
Bottom 10 Sum	4.24%	3.95%	3.93%	3.89%	3.82%	3.73%	3.69%	

There is a general increasing trend in the top 10, while the bottom 10 has a decreasing trend; furthermore, 28 states have a below than average increase. The decreasing trend of the states with below average increases may be a result of a decrease in employment. The largest decrease in percentage change in freight production is observed in NY (-12%, from 93% to 83%) and WA (-4%); NY has a decreasing forecast until the year 2025, then increases freight production but will be unable to reach year 2002 levels. In addition to NY, DC, NJ, and WA experience fluctuations: these states show a decrease between 2002 and 2010; where DC and NJ reach the year 2002 levels and continue to increase, WA only increases till the year 2015, and then faces a steep decrease. AK's freight production percentage increases between years 2002 and 2010, remains at the same level until 2020, and then shows fluctuations afterwards.

To Flow (Freight Attraction)

The trend in freight attraction increases between years 2002 to 2035, similar to the total freight production (Table 3.3).

Table 3.3: Top 10 states - freight attraction (thousand tons or ktons).

	Change in Freight Attraction						
State	2002	2010	2015	2020	2025	2030	2035
IL	149	195	229	265	310	362	419
OH	130	150	168	190	221	258	304
PA	123	149	166	187	214	249	289
IN	116	127	140	157	183	214	244
NJ	107	108	115	125	139	153	171
TX	103	120	135	153	176	204	235
GA	95	102	110	122	138	159	184
MO	90	93	99	108	123	141	164
WI	87	103	116	130	146	170	193
Top 10 Sum	1,000	1,147	1,278	1,437	1,650	1,910	2,203
Total	2,505	2,960	3,288	3,706	4,263	4,961	5,764
Top 10/National	39.92%	38.75%	38.87%	38.77%	38.71%	38.50%	38.22%

Contrary to the state ranking by change in freight production percentages, the share of the top 10 only shows a minor decrease from 38.75% (2010 value) to 38.22% (in 2035).

This indicates a stable increase for most of the states (Table 3.4). The highest increase is in the state of IL, with a 181% increase in freight attraction. Each of the top

10 states ranked highest in freight attraction show increasing trends, and higher ranked states grow with a slightly faster pace.

Table 3.4: Top and bottom 10 freight attraction percentages, 2002-2035.

	Freight Attraction							
State	2002	2010	2015	2020	2025	2030	2035	2002 Rank
IL	5.95%	6.59%	6.95%	7.16%	7.27%	7.30%	7.26%	**1**
OH	5.21%	5.08%	5.12%	5.14%	5.19%	5.19%	5.27%	2
PA	4.91%	5.03%	5.04%	5.04%	5.02%	5.03%	5.01%	3
IN	4.61%	4.30%	4.26%	4.24%	4.29%	4.30%	4.24%	4
TX	4.12%	4.06%	4.10%	4.12%	4.12%	4.11%	4.08%	6
NY	3.33%	3.06%	3.17%	3.28%	3.42%	3.60%	3.80%	10
FL	2.18%	2.92%	3.10%	3.25%	3.38%	3.51%	3.66%	20
WI	3.46%	3.48%	3.53%	3.52%	3.43%	3.43%	3.36%	9
VA	2.86%	2.77%	2.85%	3.01%	3.12%	3.28%	3.33%	13
GA	3.80%	3.45%	3.36%	3.28%	3.24%	3.21%	3.20%	7
Top 10 sum	40.43%	40.72%	41.48%	42.03%	42.49%	42.97%	43.20%	
NH	0.55%	0.58%	0.58%	0.58%	0.59%	0.59%	0.59%	42
NM	0.65%	0.67%	0.64%	0.61%	0.60%	0.59%	0.57%	39
ID	0.63%	0.60%	0.57%	0.53%	0.51%	0.49%	0.48%	40
SD	0.43%	0.45%	0.47%	0.47%	0.47%	0.45%	0.42%	43
ND	0.31%	0.36%	0.37%	0.37%	0.38%	0.39%	0.40%	46
MT	0.28%	0.32%	0.33%	0.34%	0.35%	0.37%	0.37%	49
RI	0.33%	0.33%	0.34%	0.35%	0.35%	0.35%	0.35%	44
VT	0.28%	0.29%	0.29%	0.29%	0.29%	0.28%	0.27%	48
ME	0.33%	0.30%	0.28%	0.27%	0.26%	0.26%	0.26%	45
AK	0.07%	0.07%	0.07%	0.08%	0.09%	0.10%	0.11%	50
Bottom 10 sum	3.86%	3.97%	3.93%	3.89%	3.87%	3.85%	3.82%	

IL, OH, PA, and IN rank as the top 4 in freight attraction for both 2002 and 2035, suggesting their dominant roles in freight attraction. The largest increases in freight attraction are observed in IL (5.95% to 7.26%), FL (2.18% to 3.66%), and VA (2.86% to 3.33%); the smallest freight increases are lower than 0.65% for the bottom 10 states.

Sample production freight flow and attraction freight flow maps show the strong players in each group (Figure 3.1 and 3.2, respectively), i.e. the interaction between CA, NJ, NY, MA, as well as OH, MI, IL, TX, and FL. In these maps, the freight flows are assigned by utilizing the shortest path distance between origin and destination pairs.

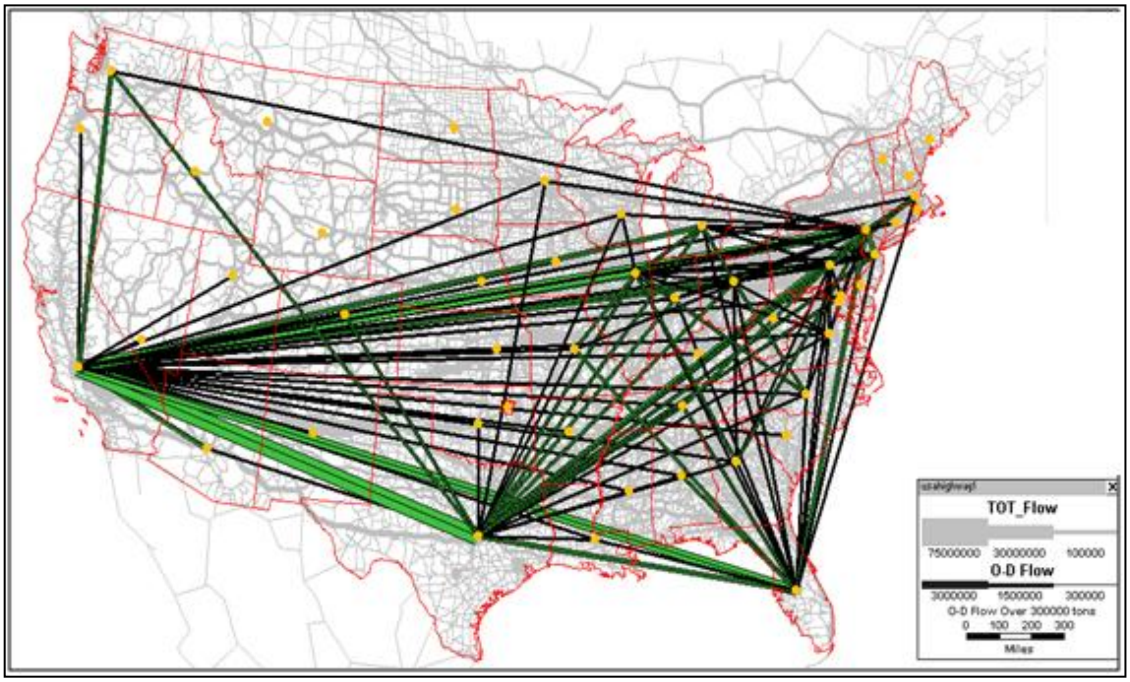

Figure 3.1: U.S. sample top state level from-to freight flows, direct lines, 2002.

Figure 3.3 gives the complete picture of the freight production and attraction at the MSA level, with 114 distinct centroids. As a result, the freight flows between regions become apparent: i.e. the Mid-American state metros of OH, MI, IL, WI, IN; New England metros of NY, NJ, MA, PA; Southern state metros of GA, TX, NC, AL, TN, and Pacific and Pacific Northwest state metros of CA, WA, OR.

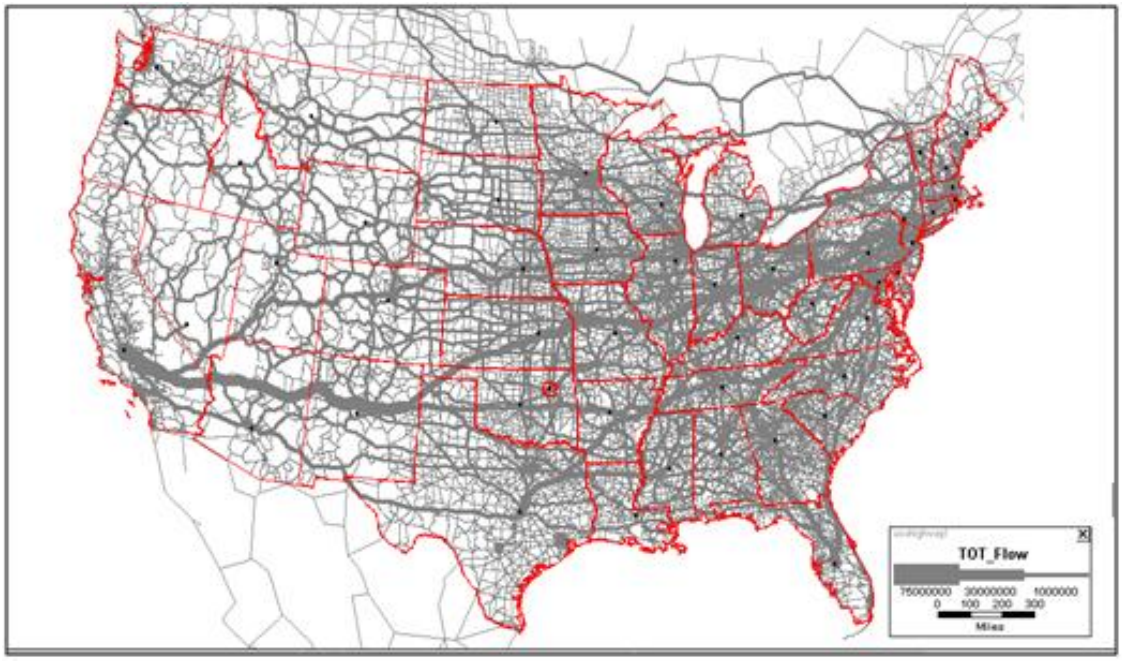

Figure 3.2: U.S. sample top state-level from-to freight flows, roadway networks, 2002.

Figure 3.3: U.S. from-to freight flows, direct lines, MSA level, 2002.

Within Flow

The average change in within freight flow is 85%, with a low of -16% (DC) and high of 232% (NY) during the study period of 2002 to 2035 (Table 3.5). In Table 3.5, the top 10 and bottom 10 states in regard to percent change of within freight through the study period is given The largest within freight flow increases are observed at CA, TX, IL, and FL; in addition, these states have a substantially larger increase compared to other states (Figure 3.4 and 3.5).

Table 3.5: Top and bottom 10 changes in within freight flows, 2002-2035.

	Change in Within Freight							
State	2002	2010	2015	2020	2025	2030	2035	2002 Rank
CA	11.00%	11.39%	11.72%	12.05%	12.46%	12.88%	13.24%	1
TX	7.88%	8.18%	8.25%	8.33%	8.48%	8.80%	9.34%	2
IL	7.51%	7.45%	7.19%	6.95%	6.72%	6.51%	6.28%	3
FL	5.51%	5.75%	5.71%	5.73%	5.71%	5.69%	5.63%	4
GA	3.61%	3.61%	3.64%	3.69%	3.71%	3.69%	3.63%	6
OH	3.90%	4.17%	4.10%	4.01%	3.87%	3.71%	3.52%	5
IN	3.00%	3.24%	3.29%	3.30%	3.25%	3.17%	3.09%	9
MI	3.12%	2.95%	2.96%	3.02%	3.05%	3.06%	3.06%	7
MN	2.72%	2.80%	2.86%	2.90%	2.93%	2.95%	2.93%	11
NC	3.08%	2.84%	2.80%	2.76%	2.70%	2.64%	2.57%	8
Top 10 Sum	51.34%	52.39%	52.52%	52.73%	52.88%	53.10%	53.28%	
WY	0.28%	0.31%	0.35%	0.38%	0.42%	0.46%	0.50%	45
WV	0.49%	0.49%	0.45%	0.42%	0.40%	0.39%	0.36%	39
NH	0.33%	0.33%	0.32%	0.32%	0.31%	0.30%	0.29%	44
ME	0.41%	0.35%	0.34%	0.33%	0.31%	0.30%	0.29%	42
AK	0.21%	0.25%	0.23%	0.23%	0.22%	0.22%	0.22%	46
HI	0.21%	0.20%	0.19%	0.19%	0.18%	0.18%	0.18%	47
VT	0.18%	0.18%	0.18%	0.18%	0.18%	0.17%	0.17%	48
DE	0.18%	0.18%	0.18%	0.18%	0.17%	0.17%	0.17%	49
RI	0.15%	0.14%	0.14%	0.14%	0.14%	0.14%	0.13%	50
DC	0.02%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%	51
Bottom 10 Sum	2.45%	2.42%	2.40%	2.37%	2.34%	2.34%	2.32%	

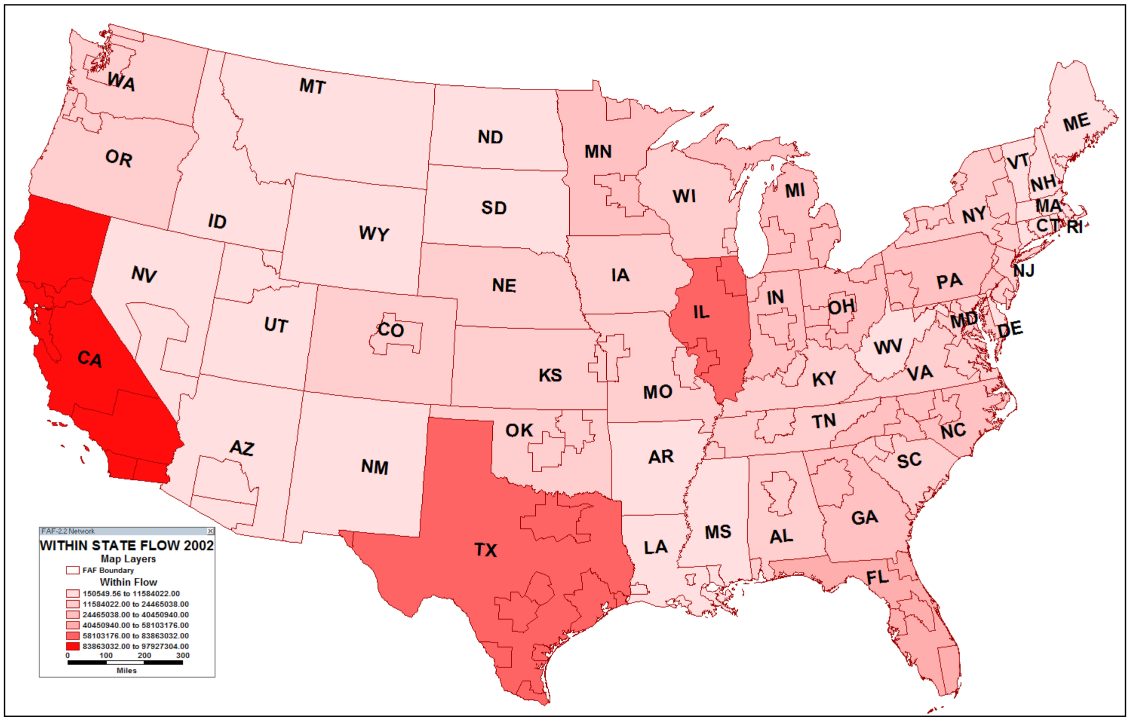

Figure 3.4: Within freight flows by state, 2002.

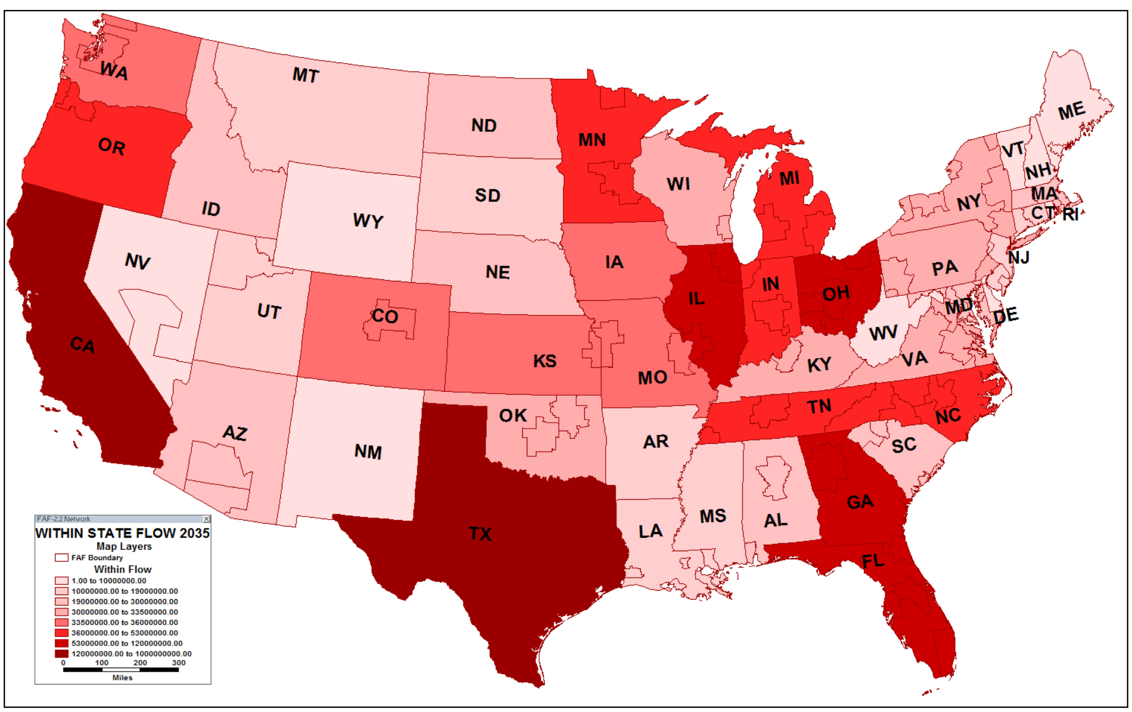

Figure 3.5: Within freight flows by state, 2035.

While the top 5 of the list show a substantial increase, the bottom 5 show a decrease over the study period. Most of the states show an increasing pattern, except the 2010 to 2015 forecasts: 70% of all states face a decrease in within freight flow during this period.

Through Flow

Through flows are identified using TransCAD, given a through state, e.g. Oklahoma, to identify the freight flows passing through the state. The highest 20 through flow states are given in Table 3.6, where IN, KY, and IL are the top 3 states carrying the largest through freight flow on their transportation networks. The top 3 states also carry 75% of all the through freight flows. The change in through freight flow from year 2002 to 2035 is 126%, with a range of 31% (FL) and 204% (NV).

Figures 3.6 and 3.7 present the spatial details of this information; darker the red, higher the through flow whereas white is no through flow. While we used the same color codes in these two figures, the freight flow totals of the year 2035 that are above 2002 levels are shown the purple color; darker the purple, higher the through flow of the corresponding state in 2035 forecasts. The highest through flows appear on the Ohio valley, showing the large freight demand of the states on the east coast.

Table 3.6: Top twenty states, through flows.

	Through Freight Flow								
State	2002	2010	2015	2020	2025	2030	2035	Rank 2002	% Change
IN	206,004	244,198	273,239	308,289	357,600	418,346	493,252	2	139%
KY	209,526	244,929	273,771	308,819	355,432	413,090	480,696	1	129%
IL	198,867	231,445	257,254	289,671	333,633	390,602	459,943	3	131%
TN	156,777	181,995	200,403	223,596	255,073	296,864	348,067	6	122%
OH	141,728	157,761	176,766	202,933	239,450	286,523	346,717	7	145%
MO	139,990	169,051	187,800	211,760	243,074	283,956	332,044	8	137%
PA	163,512	173,633	188,036	207,322	235,735	274,231	321,311	4	97%
WV	159,029	176,962	191,770	209,102	233,053	264,278	304,489	5	91%
GA	122,348	153,547	170,197	187,871	210,830	241,430	277,563	9	127%
VA	121,465	132,129	142,627	155,123	171,909	194,901	221,624	10	82%
MD	113,340	124,627	134,178	145,031	160,349	181,445	206,330	11	82%
NM	75,686	92,948	104,055	118,523	139,017	165,960	199,169	16	163%
AZ	70,639	86,339	97,635	112,343	133,039	160,728	197,839	17	180%
IA	81,049	96,480	107,237	120,563	138,658	161,988	190,245	13	135%
OK	79,162	93,954	103,716	115,838	133,606	156,919	186,489	15	136%
MS	83,335	98,379	109,495	123,224	138,976	158,554	181,950	12	118%
AL	80,752	91,818	99,916	110,578	125,105	144,086	167,599	14	108%
NJ	70,364	74,168	82,451	93,085	107,927	127,715	153,054	18	118%
AR	64,827	75,342	83,718	94,395	108,829	127,275	149,787	20	131%
TX	56,773	67,646	75,359	85,720	100,396	119,803	144,531	24	155%
Top 20 Sum	2,395,173	2,767,352	3,059,621	3,423,783	3,921,689	4,568,691	5,362,699		
Total (46)	3,209,160	3,715,933	4,107,803	4,599,917	5,269,487	6,146,558	7,210,833		
Top 20 % Sum	74.64%	74.47%	74.48%	74.43%	74.42%	74.33%	74.37%		

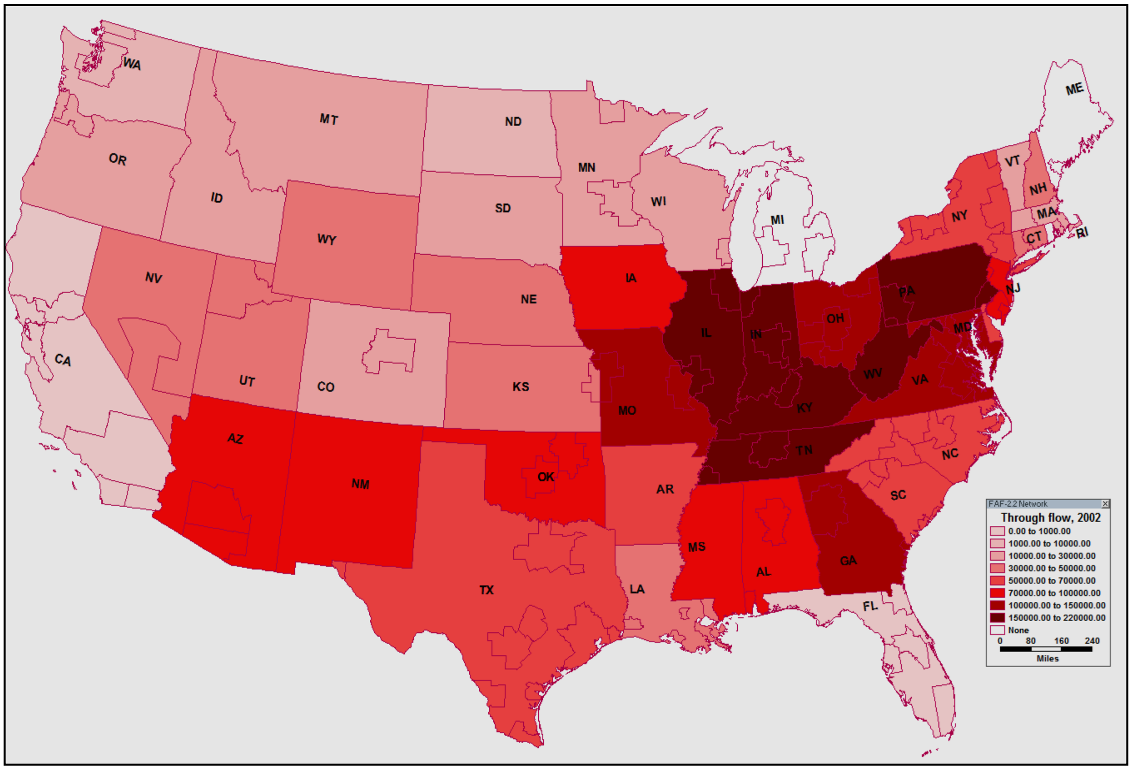

Figure 3.6: Through freight flow by state, 2002.

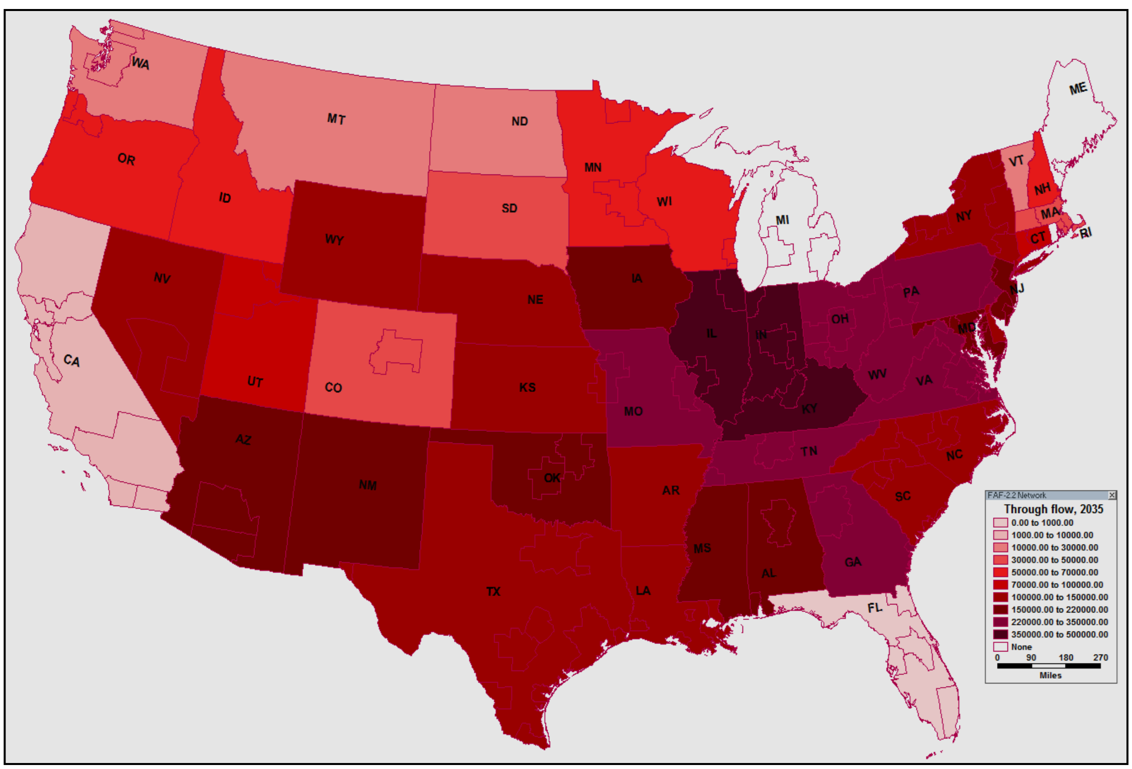

Figure 3.7: Through freight flow by state, 2035.

3.4 Freight Data Analysis at State Level

In addition to a nation-wide analysis, we can also look at specific regions or states to understand the freight behavior at a disaggregated level. In this section the freight flow pattern of the state of Oklahoma is discussed.

The freight flows From, To, Within, and Through of Oklahoma are given in Figures 3.8 through 3.11 that highlight the road usage patterns.

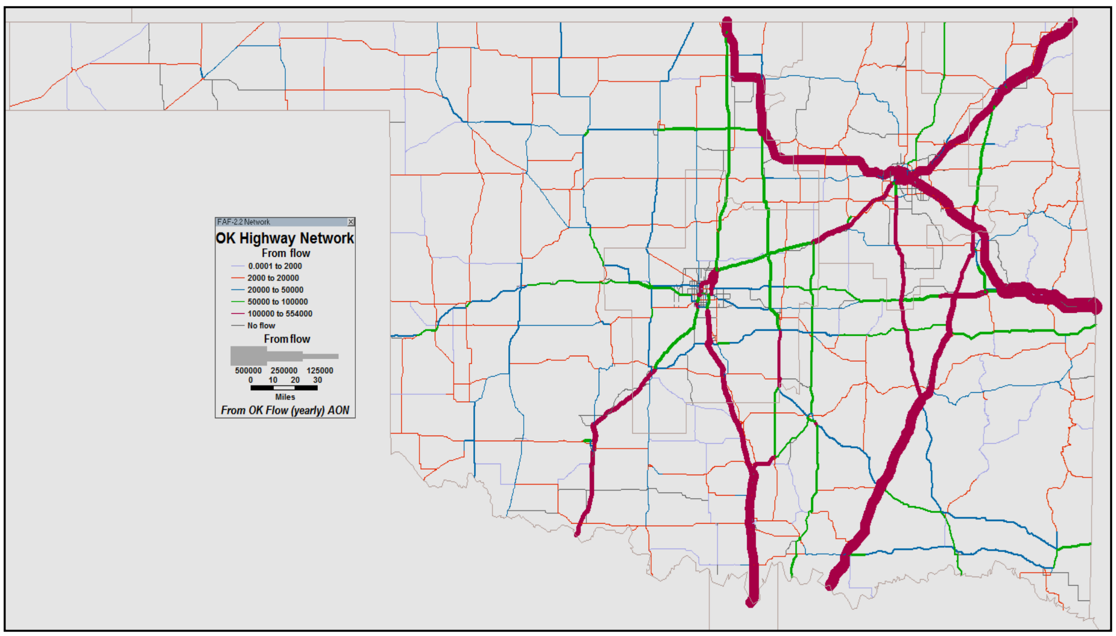

Figure 3.8: From Oklahoma freight flow, assigned on roadway network, 2002.

The Figure 3.8 shows that the freight moving out of Oklahoma uses the I-44, I-35, Muskogee Turnpike and I-75/I-65 the most. From Figure 3.9, the to Oklahoma freight flow mostly uses the I-44 and Muskogee Turnpike. The Figure 3.10 shows the highest within freight flow locations with yellow colors, at the surrounding areas of Oklahoma and Tulsa. And, the Figure 3.11 shows the through freight presence on Oklahoma roadways; in which I-40 and I-75/I-65 carry the most flows. Higher usage of these roadways will require more funding to cover the maintenance and overall upkeep.

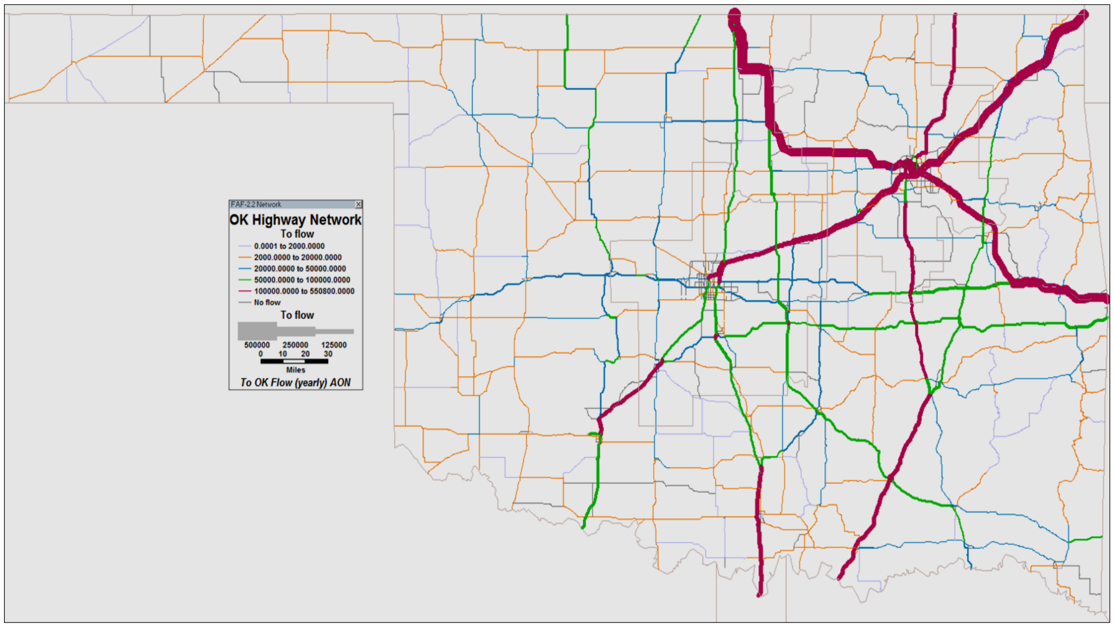

Figure 3.9: To Oklahoma flows, assigned on roadway network, 2002.

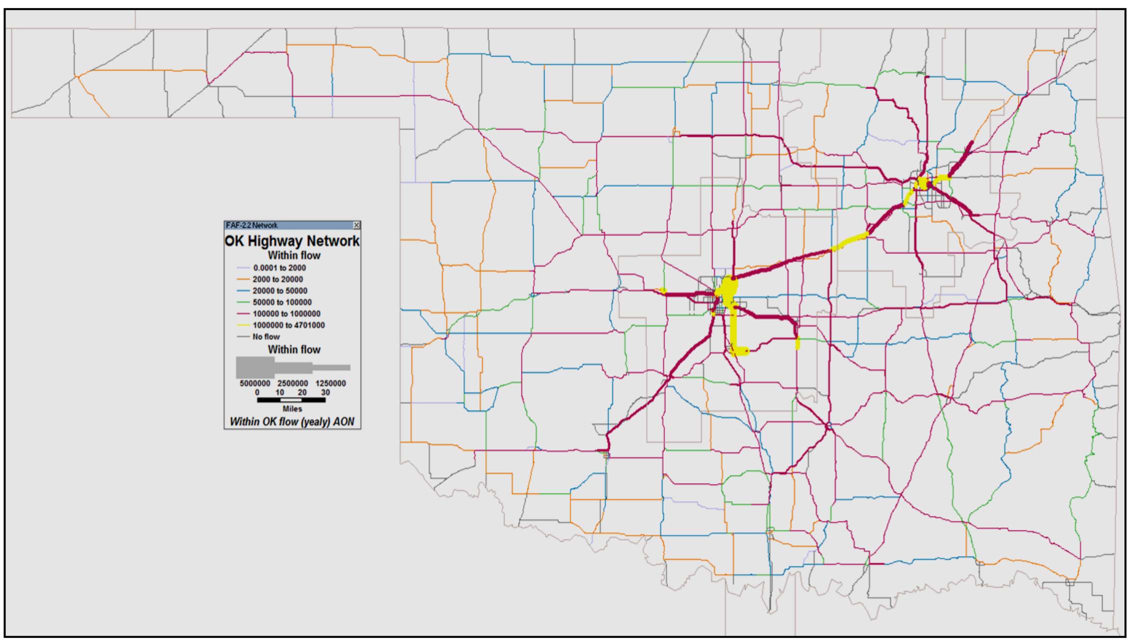

Figure 3.10: Within Oklahoma flows, assigned on roadway network, 2002.

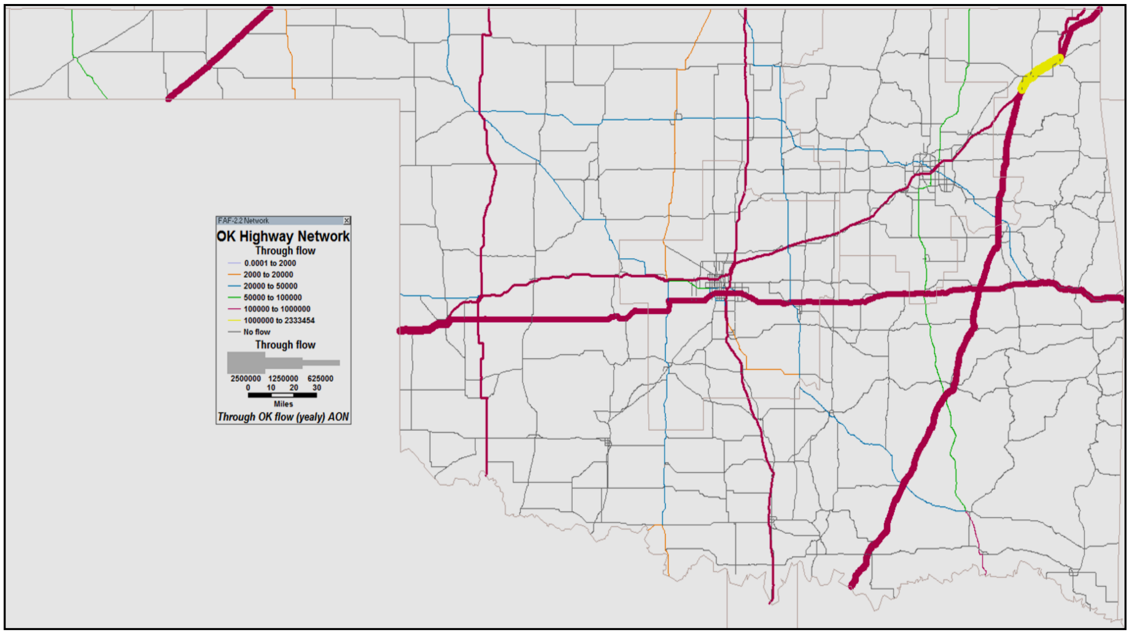

Figure 3.11: Through Oklahoma flows, assigned on roadway network, 2002.

Freight changes between years 2002 through 2035 are shown for each freight flow type in Table 3.7. In Oklahoma, similar to within freight flow in other states, 50-58% of the total freight flow corresponds to within freight flow (Table 3.7).

Table 3.7: Oklahoma from, to, within, and through flows and percentages, 2002-2035.

	Freight Flow by Type in Oklahoma						
Flow Type	2002	2010	2015	2020	2025	2030	2035
From	45,772	50,713	54,488	60,773	69,219	78,660	88,551
To	37,004	42,680	47,440	53,118	60,653	70,592	83,092
Within	235,118	240,151	256,074	278,577	306,883	338,645	370,764
Through	86,021	101,688	111,920	124,796	143,304	167,130	195,348
Flow Type	2002	2010	2015	2020	2025	2030	2035
From	11%	12%	12%	12%	12%	12%	12%
To	9%	10%	10%	10%	10%	11%	11%
Within	58%	55%	54%	54%	53%	52%	50%
Through	21%	23%	24%	24%	25%	26%	26%

When we focus on the state of Oklahoma, the role of the state is differentiated from other states. In Figure 3.12, the production and attraction relations of the state to other states are shown as direct lines.

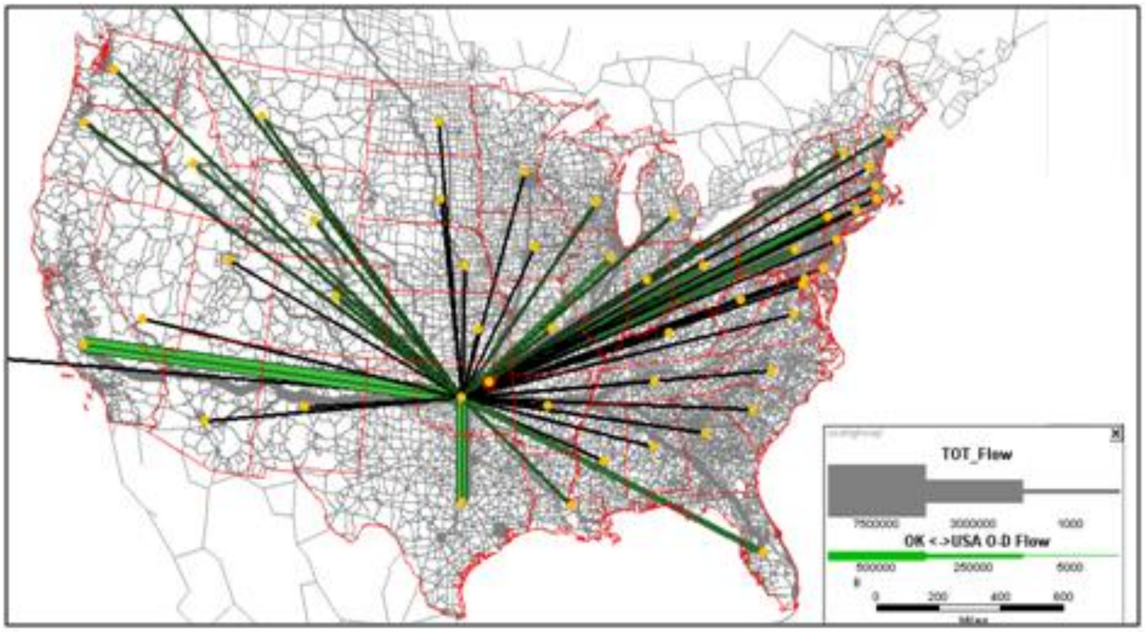

Figure 3.12: Oklahoma from-to freight flows, direct lines, 2002.

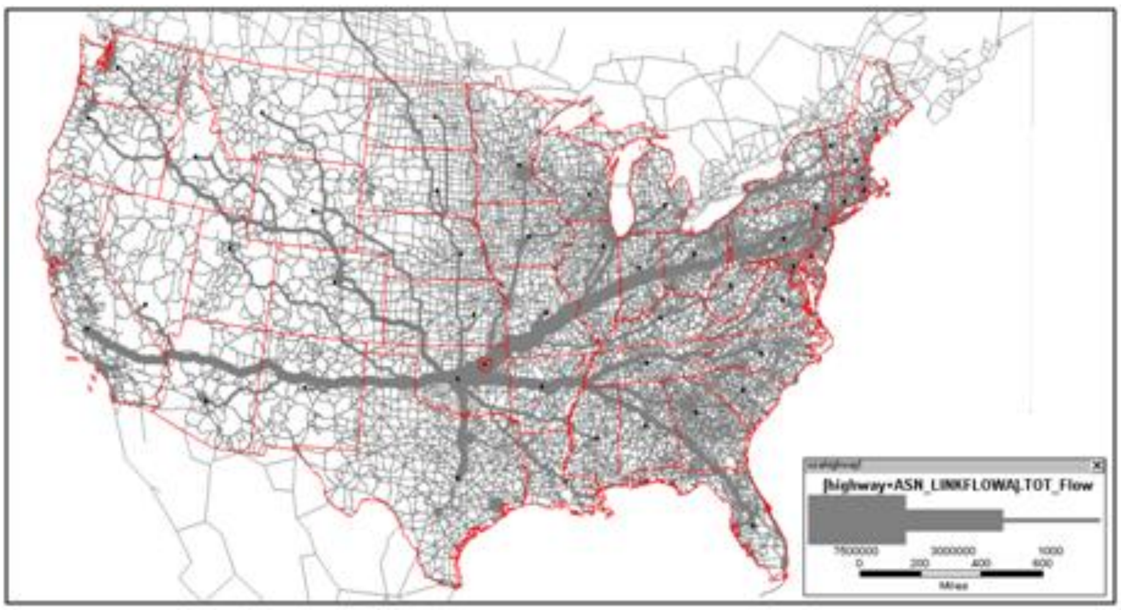

Figure 3.13: Oklahoma from-to freight flows, assigned on roadway network, 2002.

In Figure 3.13, the assigned flow is depicted which shows the large amount of freight coming from CA and stretching to the North-East states and FL.

Table 3.8 shows the top twenty OD pairs (trading partners) that move freight through Oklahoma. CA-NY ranked first in 2035, while occupying the 3rd ranking in

2002. OH-CA ranked first in 2002, but ranked 10^{th} in 2035. The listed top twenty trading partners contribute to almost 12% in 2002 to 19% in 2035 Oklahoma's total through flows. The west CA, east NY, PA, MA, NJ, FL, mid-western MI, southwest TX, and southeast FL and GA contribute the most to Oklahoma's through flows.

Table 3.8: Top twenty ODs with freight flows through Oklahoma.

Through Oklahoma Freight Flow ODs				
Origin	Destination	2002	2035	2002 Rank
CA	NY	116,472	531,250	3
CA	PA	101,971	511,371	7
CA	MD	92,660	446,035	10
CA	MA	107,468	341,613	4
CA	OH	99,078	340,667	8
CA	NJ	90,511	331,781	11
CA	FL	50,424	315,399	25
MA	FL	74,015	291,998	17
CA	GA	62,035	289,232	21
OH	CA	175,033	268,222	1
ME	FL	84,832	263,965	13
CA	IL	78,673	240,657	16
MI	CA	73,906	226,660	18
NJ	FL	94,092	224,216	9
OR	FL	40,177	219,657	32
IN	CA	102,366	218,073	6
AZ	NY	36,840	196,639	34
MI	TX	37,373	182,371	33
OH	FL	47,909	180,872	28
TX	NJ	50,952	176,946	24
Top 20 Sum		1,616,787	5,797,622	
Top 20 %		11.95%	18.92%	
Total		13,524,100	30,641,974	

At a state level, one can observe the contribution of each flow type; and in the case of through flow, we can observe the amount of traffic that originates and is destined to a different state. For example, the through freight flow map of Oklahoma is given in Figure 3.14; it shows the state's role in freight movement. Freight flow from north to south, east to west and vice versa passes through the state of Oklahoma, which is the reason Oklahoma is called a "cross-road." The highest through flows passing through Oklahoma are between TX and KS, TX and OH, TX and MO. The largest through freight flows originate from CA, TX, IL, IN, and OH, and are destined to TX, CA, KS, IL, and CO.

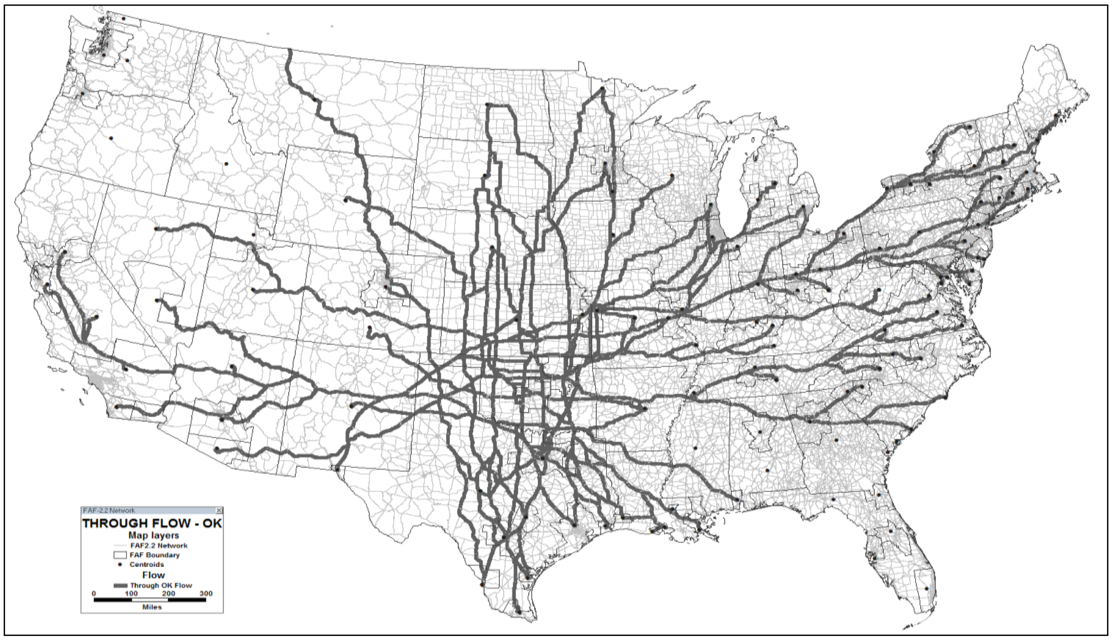

Figure 3.14: Through Oklahoma freight flows generated by all other states, 2002.

3.5 Freight Flow Measures

Production activities can be traced to the from freight flow behavior; the higher the production, the higher the freight from the region. Let's define the freight production of a state as follows:

$$s_{production} = \frac{sf_{production}}{sf_{production} + sf_{attraction}} \times 100 \quad (3.18)$$

$$s_{attraction} = \frac{sf_{attraction}}{sf_{production} + sf_{attraction}} \times 100 \quad (3.19)$$

We define a state a "freight production state" if $s_{production} > 50\%$, and a "freight attraction state" if $s_{attraction} > 50\%$.

The results of this analysis are summarized in Figure 3.15 and Table 3.9. In 2002, there existed 24 states with average $s_{production}$ of 55.78%, and in the 2035 forecast there are 27 states with average $s_{production}$ of 59.73%. The states of ID, MI, KY, and OR increase their freight production by more than 20%, whereas some states, i.e. WA (-28.62%), NY (-25.2%), and FL (-23.68%) have decreased freight production to the extent that they become attraction states during the same period.

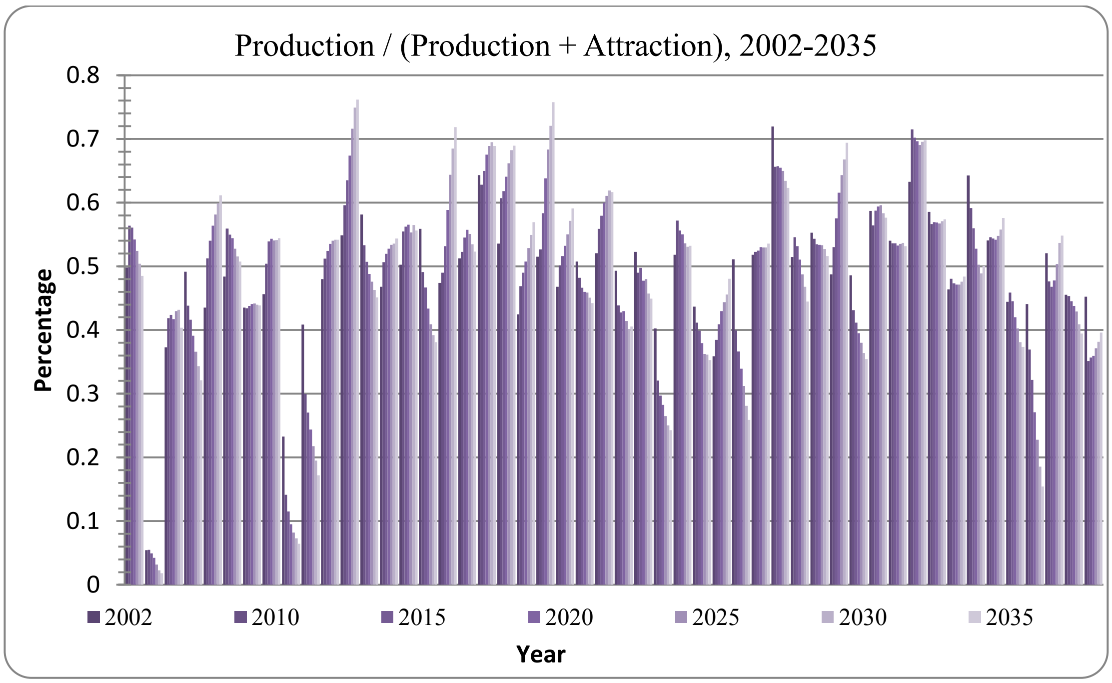

Figure 3.15: Changes in freight producing status by state, 2002-2035.

The states can be grouped into two groups according to the freight production levels; as low and high freight production states. Freight production for the states ranges from 23.30% to 71.98% in 2002 and 6.44% to 76.19% in 2035. The gap increases between 2002 and 2035, showing a polarized structure as the states with higher production freight flows increase freight production and higher attraction states increase the attraction freight flow, while decreasing attraction and production freight flows, respectively. Interestingly, the states of ID, ME, ND, and, SD have high freight production values (60%) in spite of their smaller populations as compared to other states, i.e. NY, NJ, and FL, which are the strongest freight attraction states.

Table 3.9: Top, middle, and bottom five states by producing percentage change, 2002 to 2035.

	Percentage Change of Freight Production							
State	2002	2010	2015	2020	2025	2030	2035	2035-2002
KY	47.40%	49.00%	53.20%	58.80%	64.40%	68.50%	71.90%	24.50%
MI	51.50%	52.70%	58.30%	63.80%	68.30%	72.10%	75.80%	24.30%
ID	54.90%	59.60%	63.50%	67.40%	71.60%	74.90%	76.20%	21.30%
OR	48.70%	53.00%	57.50%	61.60%	64.30%	66.80%	69.40%	20.60%
CA	43.50%	51.30%	54.00%	56.40%	58.10%	59.90%	61.20%	17.60%
…	…	…	…	…	…	…	…	…
NC	51.80%	52.30%	52.40%	53.00%	52.90%	52.90%	53.60%	1.80%
NH	51.80%	57.20%	55.60%	55.00%	53.60%	53.10%	53.20%	1.40%
LA	51.30%	52.30%	54.50%	55.70%	55.10%	53.50%	52.30%	1.00%
CT	43.50%	43.40%	43.80%	44.10%	44.20%	44.00%	43.90%	0.30%
SC	54.00%	53.60%	53.60%	53.20%	53.50%	53.70%	53.10%	-0.90%
…	…	…	…	…	…	…	…	…
AR	49.10%	43.80%	41.60%	39.10%	36.60%	34.30%	32.10%	-17.00%
KS	55.90%	49.10%	46.70%	43.40%	40.90%	39.20%	38.10%	-17.80%
FL	40.90%	30.00%	27.10%	24.40%	21.80%	19.50%	17.20%	-23.70%
NY	51.10%	40.00%	36.60%	33.90%	31.20%	28.10%	25.90%	-25.20%
WA	44.10%	37.00%	32.20%	27.10%	22.80%	18.60%	15.40%	-28.60%

Table 3.10 shows the within flow measures for the top and bottom five states listed in descending order by the 2035 percentage. While the rankings and percentages vary from 2002 to 2035, most states have a percentage of 50% or higher, meaning most states during the period are self-sufficient. In other words, at elast 50% of a state's demand is met by the state's supply. In fact, only 17 out of all states over 7 years, only 5% of all the data, in Table 3.10, or specifically DE and DC from 2002-2035, AR in 2035, and NV in 2030 and 2035, have a within flow percentage smaller than 50%. CA is the only state that consistently produces over 92% of its demand, while DC is the

only state that consistently depends on outside supply to satisfy the freight attraction that is greater than 85%. Also, the state within flow percentages range from virtually no change (i.e., SC at 73.3% in both 2002 and 2035) to a 18% change (i.e. NV at 66.6% in 2002 and 47.7% in 2035).

Table 3.10: Top, middle, and bottom five ratios of within flows, 2002-2035.

Top, Middle, and Bottom Five Ratios of Within Flows, 2002-2035								
State	2002	2010	2015	2020	2025	2030	2035	2002Rank
CA	92.70%	93.50%	93.70%	93.80%	93.70%	93.50%	93.20%	1
ND	89.70%	89.10%	89.20%	89.10%	88.80%	88.40%	88.10%	4
OR	84.30%	84.90%	85.70%	86.70%	87.10%	87.40%	87.80%	8
ID	81.80%	84.20%	85.00%	85.60%	86.20%	86.70%	87.00%	12
TX	87.10%	87.50%	87.20%	86.90%	86.50%	86.40%	86.70%	5
WA	85.60%	84.60%	82.70%	80.50%	78.00%	75.00%	72.00%	7
IL	81.60%	79.60%	77.70%	76.00%	74.30%	72.60%	71.20%	13
KY	62.60%	62.40%	64.50%	66.90%	69.10%	69.90%	70.50%	44
IA	71.00%	73.20%	72.70%	72.40%	71.30%	70.70%	69.70%	29
TN	73.90%	72.90%	72.60%	71.90%	70.90%	70.00%	69.20%	24
NJ	60.00%	60.80%	59.60%	57.50%	55.00%	52.90%	50.30%	46
AR	64.50%	61.80%	59.60%	56.90%	53.90%	51.10%	48.20%	42
NV	66.60%	60.90%	58.10%	56.00%	52.60%	49.60%	47.70%	40
DE	44.90%	46.50%	49.40%	48.30%	45.80%	44.20%	43.20%	49
DC	15.30%	3.60%	3.50%	3.10%	3.00%	2.90%	2.80%	50
Average	73.30%	72.30%	71.90%	71.30%	70.30%	69.30%	68.40%	

While DC and CA have the lowest and highest within flow percentages, respectively, as shown in Table 3.10, when it comes to through flow percentages, DC and CA have the top and bottom percentages, respectively. Almost all states have a through flow with the exceptions of WA, FL, CA AK, ME, MI, and RI whose through flows are zero due, and main reason is that these states are corner states. Spatially, the states with higher through flow percentages are mostly the non-coastal/non-border states, and the coastal or border states have smaller through flow percentages. Some states have increasing percentages, while other states have decreasing percentages from 2002 to 2035; however, the variations are small in the range of -4.8% (ND) to 8.3% (WA).

3.6 Regression Results

Linear regressions, equations given in 3.14 through 3.17, are run with the 2002 base-year economic factors, such as employment, number of establishments, payroll, and revenue (or sales) as independent variables and the total from, to, within, and through flows at the state level as the dependent variables. The back elimination process is used to identify the best regression, and the results are summarized in Table 3.11.

The results from initial runs, with all variables included, are included in Table 3.12 with non-shaded cells. The variable Through Freight in all cases is not significant, as indicated by *p*-values of more than 41%. The shaded cells show the significant results for the four regression models without the through flow variable. The models are statistically significant as evidenced by R-square values ranging from 87% to 89.9%, and p-values of 95% or more. Also, as expected, the coefficients of the independent variables From Freight and Within Freight are all positive since they contribute directly to the employment, number of establishments, payroll, and revenue of the transportation industry. Since the To Freight of a state is more likely shipped by transportation firms outside that state, the independent variable To Freight has a negative coefficient.

Table 3.11: Results of regression of freight flows and socio-economic indicators, 2002.

		Regression Results				
Variables	Statistics	From Freight	To Freight	Within Freight	Through Freight	R-Square /Intercept
Establishment (EST)	Coefficient	0.06	-0.044	0.016	0	0.898615/
	T-Stats	3.588	-2.883	6.232	0	292.7481
	P-Values	0.001	0.006	0	1	
	Coefficient	0.06	-0.044	0.016		
	T-Stats	3.651	-2.988	12.076		0.898615/
	P-Values	0.001	0.005	0		292.7547
Employment (EMP)	Coefficient	1.414	-1.057	0.34	-0.525	0.881085/
	T-Stats	3.814	-3.138	5.776	-0.229	-1585.11
	P-Values	0	0	0.003	0.82	
	Coefficient	1.405	-1.041	0.328		0.880929/
	T-Stats	3.855	-3.2	10.808		-1347.29
	P-Values	0	0.003	0		
Payroll (PAY)	Coefficient	43.795	-33.893	11.179	-3.482	0.878229/
	T-Stats	-3.02	3.547	5.71	-0.046	-79816.5
	P-Values	0.001	0.004	0	0.964	
	Coefficient	43.738	-33.783	11.103		0.878223/
	T-Stats	-3.12	3.604	10.989		-78238
	P-Values	0.001	0.003	0		
Revenue (REV)	Coefficient	125.75	-110.002	36.379	188.856	0.900412/
	T-Stats	3.379	-3.252	6.164	0.822	20996.09
	P-Values	0.002	0.002	0	0.416	
	Coefficient	128.844	-115.949	40.517		0.898729/
	T-Stats	3.493	-3.523	13.193		-64610.4
	P-Values	0.001	0.001	0		

3.7 Discussions and Future Research Directions

In this chapter we show that the set of measures, from, to, within, and through freight flow of states present a different perspective to understand the dynamics of state economies. Based on the FAF$^{2.2}$ data, the states of IL, MI, and KY are the top 3 in total all-commodity production flow; DC and AK are the lowest freight production flow states. The states of IL, OH, and PA share the top 3 in freight attraction flows, where

VT, AK, and ME have the lowest attraction flows. Production and attraction freight flows fluctuate through the study interval, 2002 to 2035, while the total for the U.S. increases.

The dynamic change in this classification shows the dynamic nature of state economies. Within freight flow is proportional to the population; therefore, states with larger populations, CA, TX, IL, and FL typically have very high within freight flows compared to the states with smaller populations, such as DC, AK, and RI.

As a state becomes a strong producing state, we can expect it to have a stronger economy, at the same time less dependence on other states. This indicator can be used, for instance, to judge the state's likelihood to be impacted from the fluctuations (i.e. due to an extreme event) in other states.

The highest through flow carrying states are IN, KY, and IL. Clearly, the transportation networks of these states are used to transport the freight flows resulting from the high productions and attractions from other state pairs who have freight interactions. Typically, the higher the through flow a state has, the more it is used as the "cross-road of America." States contributing more through flows can be regarded as benefiting from other states. States with a higher through flow may need to consider more federal funding to upgrade their highway networks, or they may consider charging through traffic tolls for out of state through freight, though this is a politically sensitive topic worthy of further research.

In this chapter, the role of freight in our economy is discussed and analyzed, using the $FAF^{2.2}$ data. Freight flows are good reflections of the national and local economies. Indeed, the regression models explaining freight flows by employment, establishment, revenue, and payment are statistically sound, particularly for state-level production, as shown by attraction and within flows with *R*-square values between 87.8% and 89.9%. Hence, we can successfully explain and forecast these variables using the freight data. The regression results for state through flows are not significantly explained by the same set of state economic indicators, opening the door for future models with better variables.

The following chapter analyzes the freight flow movement under extreme event conditions. In spite of the invisibility of challenges, freight transportation plays an important role especially before, during and after extreme events. We present a framework to analyze such cases, and demonstrate with three different extreme event scenarios.

Chapter 4: Freight and Extreme Events

A Retro-Analysis of the I-40 Bridge Collapse on Freight Movement in the U.S. Roadway Network using GIS and Assignment Models

Extreme events damage transportation networks; one such disaster is a bridge collapse. When a bridge fails to function, then not only the passenger flow but naturally the freight flow is affected. The traffic poses negative impacts on local, regional and national economy. In this chapter, we examine the spatial and economic impact of the 2002 I-40 Bridge Collapse (Oklahoma, U.S.) on the freight movement on the roadway network. We approach the scenario from two perspectives; first model presents the immediate disaster conditions, and second to provide guidance in reroute planning after the disaster. We use the $FAF^{2.2}$ database, TransCAD software, and two assignment models (AON and UE) to analyze the impact of the disaster on the freight flow. The results show that the bridge collapse did not only impact the freight flows on nearby highway network links, but also affected flows on links further away from the bridge. Consequently, we show that the conventional models, which rely on gravity-based spatial distance decay effects, often overestimate the nearby affects, whereas underestimate the further-out freight flow changes on the network.

This chapter is adopted from Aydin [2009], and presented here to establish the background and continuum of topics.

4.1 Literature Review

The U.S. has its own record of bridge disasters: the 1967 Silver Bridge collapse on the Ohio River between Ohio and West Virginia, the 1983 Mianus River Bridge collapse in Connecticut, the 1987 Schoharie Creek Bridge in New York, the 1989 Hatchie River

Bridge in Tennessee, the 1994 Northridge earthquake, the 1995 Arroyo Pasajero Bridge in California, the 1995 Kobe earthquake, the 2002 I-40 bridge collapse in Oklahoma, the 2005 Hurricane Katrina, and the I-35 Bridge in Minneapolis over the Mississippi River in 2007. The damages to these bridges marked the history with the resulting economic loss and lives unfortunately lost.

Parallel to the increasing number of disasters each year, there has been an increasing research in effects of disasters. The reason behind the increase in number of disasters is partially because of an actual numerical increase and partially because we have more capable technology; facing extreme events surfaced topics such as emergency planning: how to prepare for extreme events, how to avoid or act upon. Generally, the focus has been on the direct physical, social, and demographic damages, which is covered by the media and has attracted the attention of the research community. However, the direct and secondary damages to transportation systems, or any other lifeline systems (water, electricity, etc), are hardly negligible. For instance, the I-35 Bridge in Minneapolis over the Mississippi River collapsed in 2007, as a result of which a $220,000/day loss is estimated. [Xie and Levinson, 2008]. Authors conclude that 20% of this loss can be attributed to freight trips and that the bridge collapse caused significant changes in overall traffic conditions.

One of the early studies that analyzed the effect of extreme events on the lifeline system performance is by Chang and Nojima [2001]. Authors analyzed the 1989 Loma Prieta, the 1994 Northridge, and 1995 Hyogoken-Nanbu (Kobe) earthquakes. Authors show a high correlation between the traffic recovery and the functional highway sections, functional highway length, and significance based measures. Rose and

Benavides [1999] measure regional impact of a hypothetical earthquake in Memphis area that disrupts the electricity distribution. Authors account for the indirect costs and forecast a 7% loss of Gross Regional Product due to this hypothetical earthquake. Chang [2003] uses gravity-based performance measures of accessibility to determine the overall and distributional effects of extreme events on urban transportation systems. Assuming only transportation network changes, analyses focus on the spatial disparities in loss and implications of alternative restoration principles.

4.2 Methodology

In this section we present the performance measures and the assignment approaches we use in our models, as well as how the economic impact of the I-40 Bridge collapse on the freight flow movement is calculated.

Performance Measures

Vehicle Miles Traveled (VMT) and Vehicle Hours Traveled (VHT) measures are widely accepted aggregated measures. VMT measure is based on distance (4.1) and VHT measure is based on time (4.2). We also use Volume over Capacity Ratio (VCR) and Weighted Average Freight Difference (WAFD) measures, which we define for each link as disaggregated measures. VCR takes the capacity of the link into account and is used to define congestion on that link; the higher the VCR, the higher the congestion on the corresponding road segment (4.3 and 4.4).

$$VMT = \sum_l v_l d_l \tag{4.1}$$

$$VHT = \sum_l t_l d_l \tag{4.2}$$

$$VCR = v_l / C_l \tag{4.3}$$

$$t_l = t_0 \left[1 + \propto (VCR_l)^{\beta}\right] \tag{4.4}$$

where, v_l is the link flow volume and d_l is the length of link l of the network; t_l is the link travel time; C_l is the capacity of link l, α and β are parameters.

We analyze the changes in these measures to model the freight behavior under extreme events. A positive change in these measures are indicators of a disaster's negative impact on freight movement, by increasing time, distance traveled and by increasing congestion. For instance, *VMT*(post-disaster)/*VMT*(pre-disaster) > 1, then we can say the freight-miles increases; =1 is no change; <1 is the freight-mile decreases after the disaster. Similar analogy can be given for VHT as well.

We also classify VCR ratios into four categories:

- $VCR < 1$: under capacity usage of the road,
- $1 < VCR < 2$: medium-severe congestion,
- $2 < VCR < 4$: severe congestion, and
- $VCR > 4$: completely congested.

We calculate WAFD as the product of the absolute difference of pre-and post-disaster total flow on a link times the length of the link. In this case, the higher the WAFD, the higher the effect of the disaster on the freight flows for a particular link. *WAFD* is defined for each link, *l*, as in (4.5):

$$WAFD_l = \left| v_{l,post} - v_{l,pre} \right| * d_l \tag{4.5}$$

where $v_{l,post}$ and $v_{l,pre}$ are the flows and d_l is the length of link l.

Other attributes that are available from the FAF include the FCLASS and RUCODE classification of roads. FCLASS groups the road segments based on the functionality, e.g. interstates, major arterials, minor arterials, or others. RUCODE classifies the road segments based on the population of the area it is located in:

- RUCODE =1, if rural
- RUCODE =2, if small urban area (population of 5,000 to 49,999)

- RUCODE =3, if small urbanized area (population of 50,000 to 199,999)
- RUCODE =4, if large urbanized area (population > 200,000)

We incorporate these attributes into our model to analyze the scenario results and provide a detailed perspective on disaster effect on freight flow at different levels.

Assignment Approaches

The first approach (Approach I) models the scenario in such a way that the freight flow already adopted to the changes caused by the disaster, by using the available network. In the AON algorithm, only the distance is considered for the path decision; while in the UE algorithm both distance and time are factored. By comparing the pre-disaster approach I to post-disaster approach I, we model the change in freight flow due to the reroutes caused by the disaster.

In addition to the first approach, we should also model the freight movement immediately after the disaster. We use a second approach (Approach II) to model the 'uninformed' users' path decision: at this time, the users are not aware of the bridge collapse, therefore, are still planning on utilizing a route that include the now-collapsed bridge to reach their destination. Once a user receives the information that 'the bridge is collapsed,' the user is unavoidably pressured to use the closest link from the disaster area, even though the link is already occupied.

This is one frequent case, for instance at times of emergency evacuations. In spite of the high congestion, the population is urged to leave through already congested roadways. Improved evacuation models should account for the road capacity and provide alternate ways to accommodate the population to be evacuated.

In the application of the second approach, we use the critical link analysis method in TransCAD, where we split the freight flow as given in 4.6:

$$\sum_{l}^{N} x_l = x_{l=b} + \sum_{l \neq N} x_l \tag{4.6}$$

or as given in 4.7:,

$$T = T_{l,b} + T_{nb} \tag{4.7}$$

where x_l is the flow on link l, $x_{l=b} = T_{l,b}$= is the flow on the bridge link b under the pre-disaster condition. T is the total flow on all links; T_{nb} is the total flow without the bridge under the pre-disaster condition, N is the total number of links of the network.

In second approach capacity is an important element, since we are modeling the spread of the freight flow that used the bridge in the pre-disaster scenario in the post-disaster case. Hence, we only use the UE algorithm for pre- and post-disaster comparisons.

Economic Impact of I-40 Bridge Collapse

We use a straightforward approach to calculate the economic impact of the I-40 bridge collapse on the freight movement by using the ratio of the Gross State Product (GSP) and the ton-miles. The Bureau of Transportation Statistics estimates this ratio as 26.6 cents per ton-mile for the year 2001 [USDOT BTS, 2009]. We use a linear regression model to estimate the economic impact by stating the positive linkage between the GSP of a state and the total assigned freight flow on the network links of this state. Specifically we use a linear relationship with a logarithmic transformation of the *GSP* and Pre-UE total state flow (*TSF*) (4.8), where *s* is the index for states, E_s is the standard error:

$$\ln(GSP_s) = A + B \ln(TSF_s) \pm 2E_s \tag{4.8}$$

4.3 I-40 Bridge Collapse Case Study

For this case study we use the highway network and the freight data provided in FAF$^{2.2}$. The MSA level freight data is disaggregated to county level for Oklahoma, with the methodology previously described in chapter 3.

The I-40 Bridge is located 40 miles from the Arkansas border, on a major east-west route that is used by an estimated 20,000 vehicles/day in year 2002. On May 26, 2002, the bridge collapsed after being hit by a barge, which resulted in congestion up to 12 miles. Even though the traffic was re-routed, the enormous traffic congestion was relieved only after the bridge partially re-opened two months after the incident on July 29, 2002. It took an additional six to eight weeks to open all the lanes and normalize the traffic. At the time media called the I-40 Bridge collapse is the 3rd worst bridge collapse in the U.S., because of the 14 fatalities, and the collapse of the approximately 500-ft-long bridge section [Colberg, 2002]. Oklahoma state officials estimated a $30 million economic loss in repairs and lost revenue that Oklahoma taxpayers had to pay due to the bridge collapse.

4.4 Freight Flow Changes in Oklahoma due to the I-40 Bridge Collapse

Approach I, pre- and post-disaster comparison, AON

The AON algorithm (which is based on the shortest distance) shows a 35.72% (2,001 miles) increase in usage of the OK roadway network after the bridge collapse. If we only look at the roadway network in Oklahoma, we see that 62.63% of the roads have increased freight flows, whereas the 37.37% of the roads have decreased freight flows. In Figure 4.1 we show the positive change in freight flow with orange, pink, red and negative change in freight flow with blue, green, and purple colors, and the width is an indicator for the absolute value of change, larger the higher. The largest change occurs on the road segments surrounding the bridge, but the entire I-40 (the east-west blue colored line) shows a decrease, whereas I-44 shows an increase. This suggests that, after the bridge collapse, freight flow shifted from I-40 to I-44.

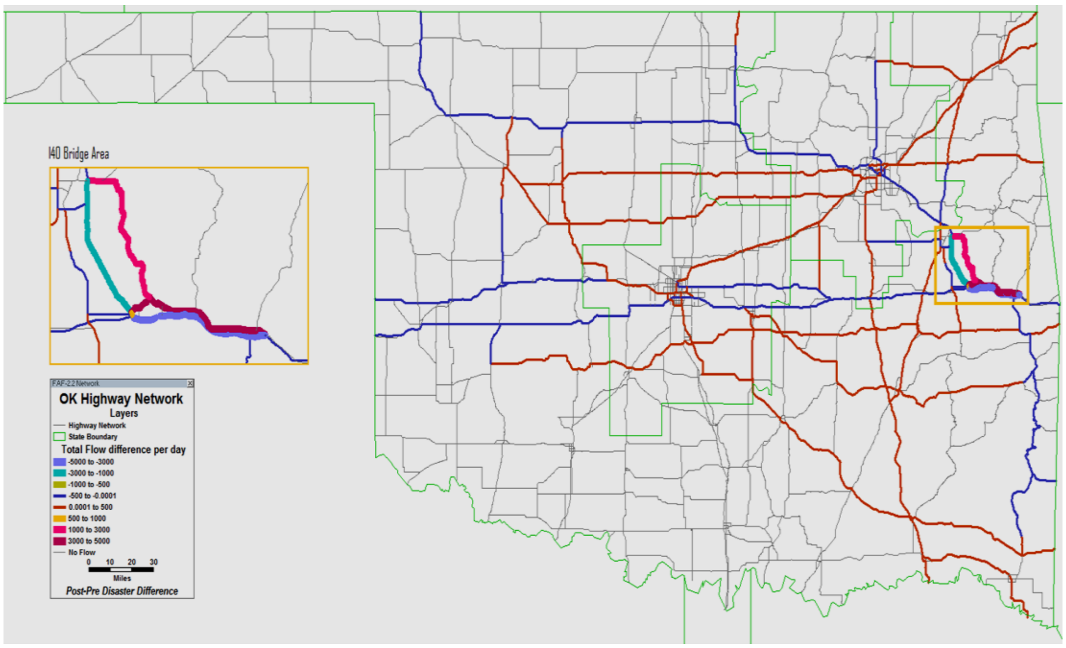

Figure 4.1: Post-pre disaster flow differences under AON assignment.

Approach I, pre- and post-disaster comparison, UE

The UE algorithm results in a higher change than the AON algorithm, by showing change in flow on the 89% (7,975 miles) of the OK roadway network. The increased freight flow is about 45%, and the decreased freight flow 43% of the total change. This translated to a decrease in freight flow for the overall OK roadway network. Based on the results, the highest change occurs in the roadways surrounding the bridge, and comparable increases evident on I-44 (Figures 4.2 and 4.3). The I-40 corridor shows decreased freight flows, an increased freight flow on I-44, and I-35 shows a decrease north of the bridge and increased flows in the remaining sections. This suggests that the flow shifted from I-40 to I-44, which, as a result of the disaster, increased freight traffic.

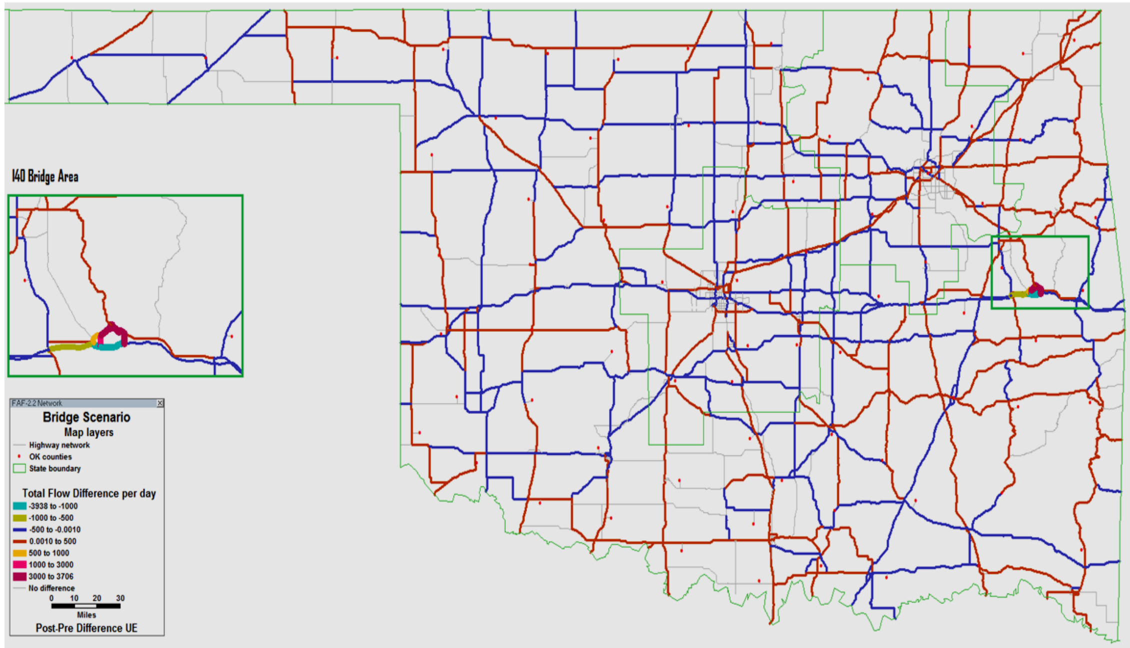

Figure 4.2: Post-pre disaster flow differences under the UE assignment.

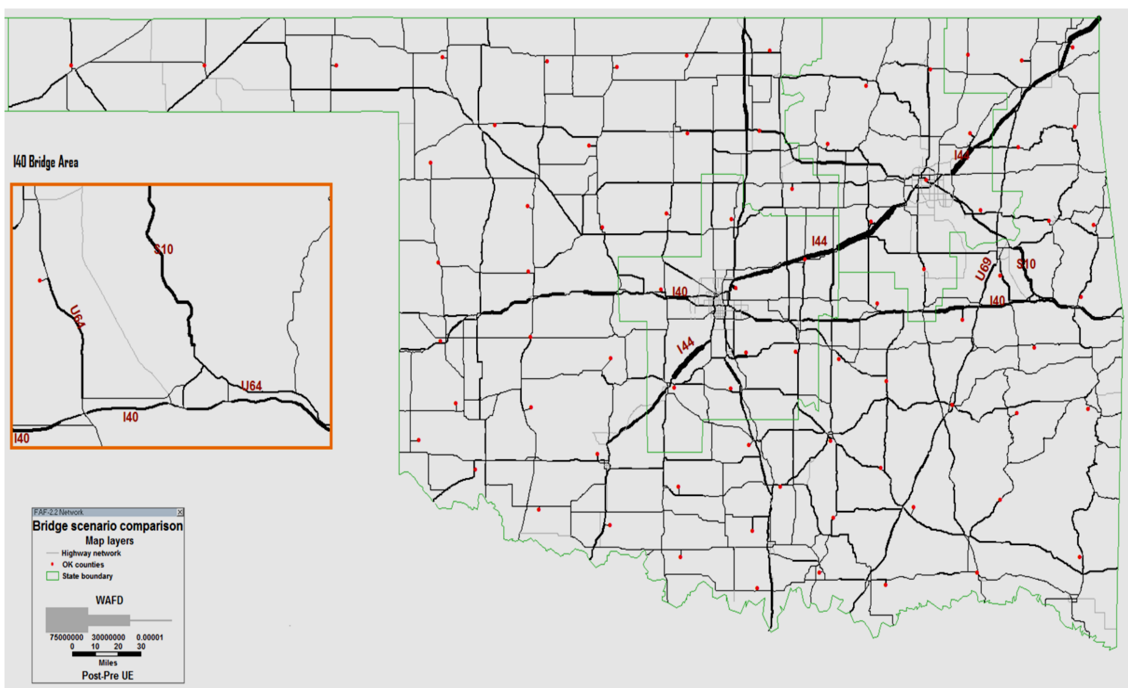

Figure 4.3 Post-pre disaster WAFD under the UE assignment.

The Table 4.1 presents the pre-disaster and post-disaster comparison of the VCR measure by the FCLASS and RUCODE classification of the roadway network. The results suggest that major arterials are not congested, whereas 0.073% of all minor arterial miles and 0.347% of all other road miles are highly congested, in addition to the 0.012% of interstate miles that are severely congested. Therefore, the freight flow changes affected the minor arterial and other classified roads more than the interstate and major arterial classified roadways.

Table 4.1: Pre-Post Disaster VCR Changes, UE, FCLASS/RUCODE OK.

FCLASS				
Congestion	**Interstate**	**Major Arterial**	**Minor Arterial**	**Others**
Under Capacity	0.40%	0.11%	-0.07%	-0.35%
Medium-Severe	-0.41%	-0.10%	0.07%	0.23%
Severe	0.01%	0.00%	0%	0.11%
Most Severe	0%	0%	0%	0%
RUCODE				
Congestion	**Urban**	**Small Urban**	**Small Urbanized**	**Large Urbanized**
Under Capacity	-9.48%	0.72%	-14.81%	10.45%
Medium-Severe	9.22%	-0.78%	10.40%	-6.92%
Severe	0.26%	0.06%	4.41%	-3.54%
Most Severe	0.00%	0.00%	0.00%	0.00%

The most interesting result from the Table 4.1 is based on the FCLASS attribute, the VCR value of 'under capacity' on interstates increases, suggesting there is a slight shift from interstate classified roads to other categories in Oklahoma. The results for the RUCODE attribute show that RUCODE=1 and RUCODE=3, rural area and small urbanized area coded roads have increased congestion in the post-disaster case.

Approach I vs. II, post disaster comparison, UE

The difference between the two approaches is that the first approach assumes that the users acknowledge the collapsed bridge, thereby making adjustments to their routes to minimize their costs in the post-disaster network. However, in the second approach, users are not aware of the collapsed bridge and are unable to create a route with this new information. As a result, the flow previously using the collapsed bridge overflows onto the freight flow that is already occupying the network in the post-disaster case. We expect to have a lower congestion result with the first approach due to the informed decision made by the users.

Table 4.2: VCR Values under Approach I vs. Approach II

	OK		**U.S.**	
Congestion	Approach I	Approach II	Approach I	Approach II
Under Capacity	90.16%	88.95%	84.30%	82.88%
Medium-Severe	10.71%	9.17%	14.70%	14.12%
Severe	0.43%	1.88%	2.43%	2.79%
Absolutely	0.00%	0.00%	0.21%	0.21%

We compare the congestion in the network for Oklahoma (Table 4.2 left section), the second approach results in a higher congestion value (0.43% vs. 1.88%). The first approach suggests that there are slightly higher uncongested roads (under capacity 90% vs. 89%). As expected, the first approach resulted in a lower congestion for the network.

4.5 Freight Flow Changes in U.S. due to the I-40 Bridge Collapse

Approach I, pre- and post-disaster comparison, AON

After the disaster, freight flow also changes on other parts of the network. Based on the AON algorithm results, 13% of the freight flows on the U.S. roadway network change to a different path (link) after the disaster. 64% of this change is a freight flow increase, and the remaining 36% is a freight flow decrease on paths. The spatial distribution of this change shows itself as a decrease along the I-40 corridor and increased flows on parallel roads, given in Figure 4.4.

The Figure 4.4 also shows the extent of freight flow changes in Oklahoma, as well as in the U.S. roadway networks, in that the disaster also affected the freight flows outside of the Oklahoma roadway network by shifting the freight movement out of the state. Flow pattern spreads over the network from California at the West coast and in DC at the East coast. Both VMT and VHT measures increase in the post disaster case (0.0047%), confirming the increased cost in terms of miles and time traveled.

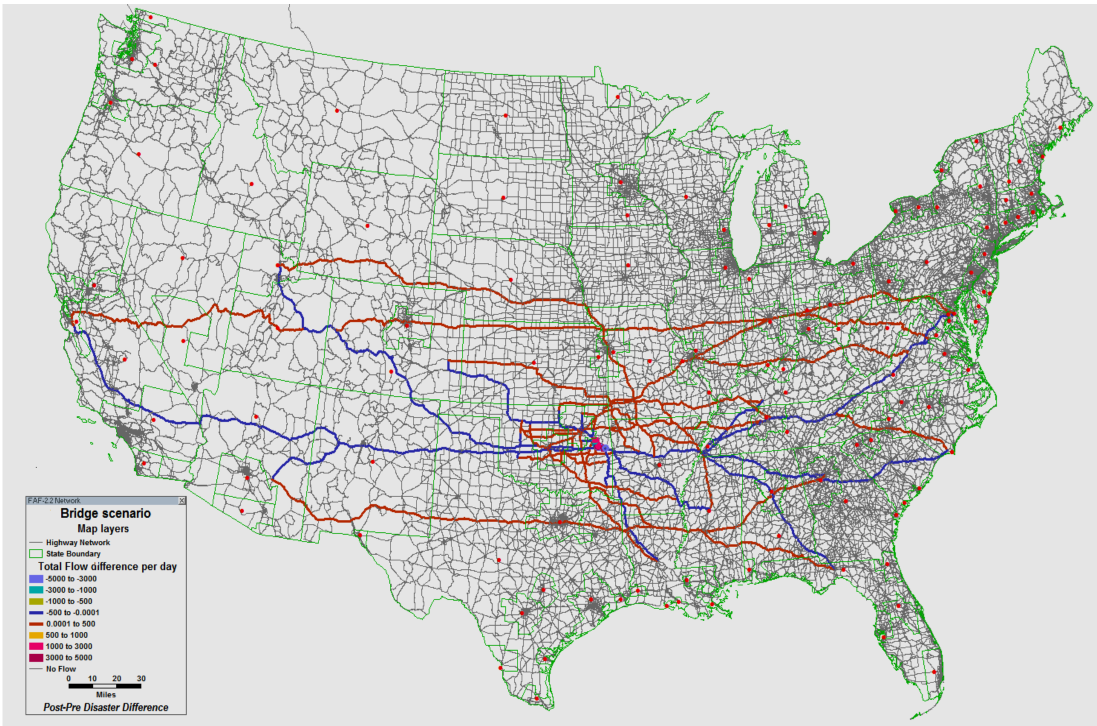

Figure 4.4: Post-pre disaster flow differences, AON, U.S.

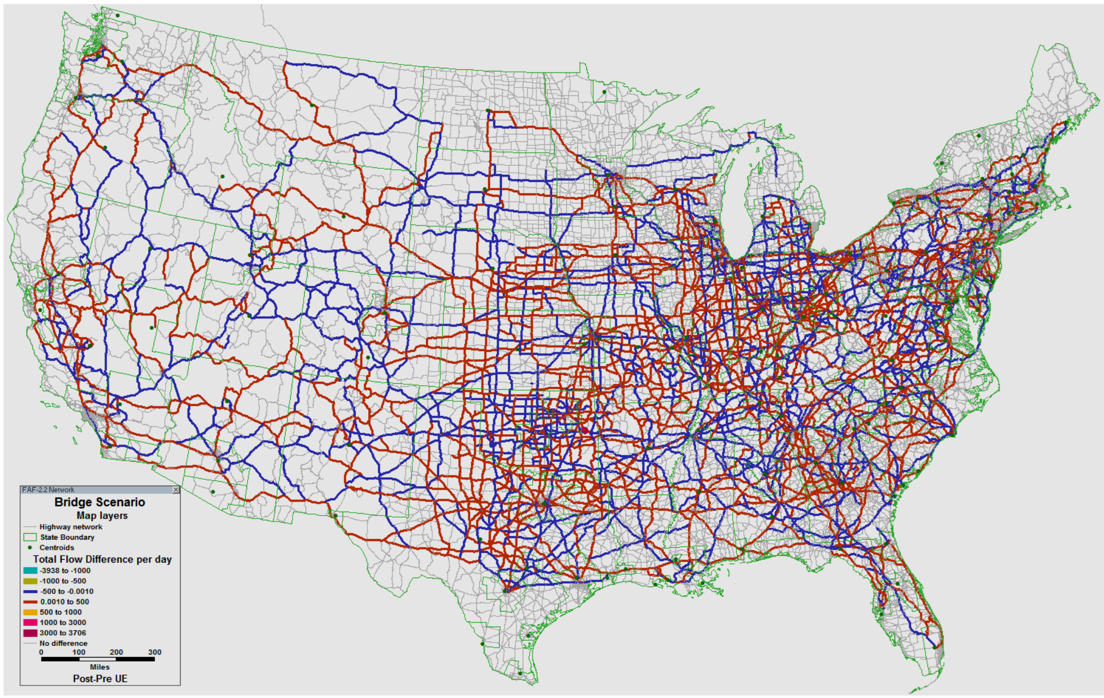

Figure 4.5: Post-pre disaster flow differences, UE, U.S.

Analysis of each link for the changes, WAFD, presents the extensive changes on the U.S. roadway network in Figure 4.6, where the line-width indicates the severity of the impact. This figure also shows the effect of the bridge collapse in OK, but also at other sections of the U.S. roadway network.

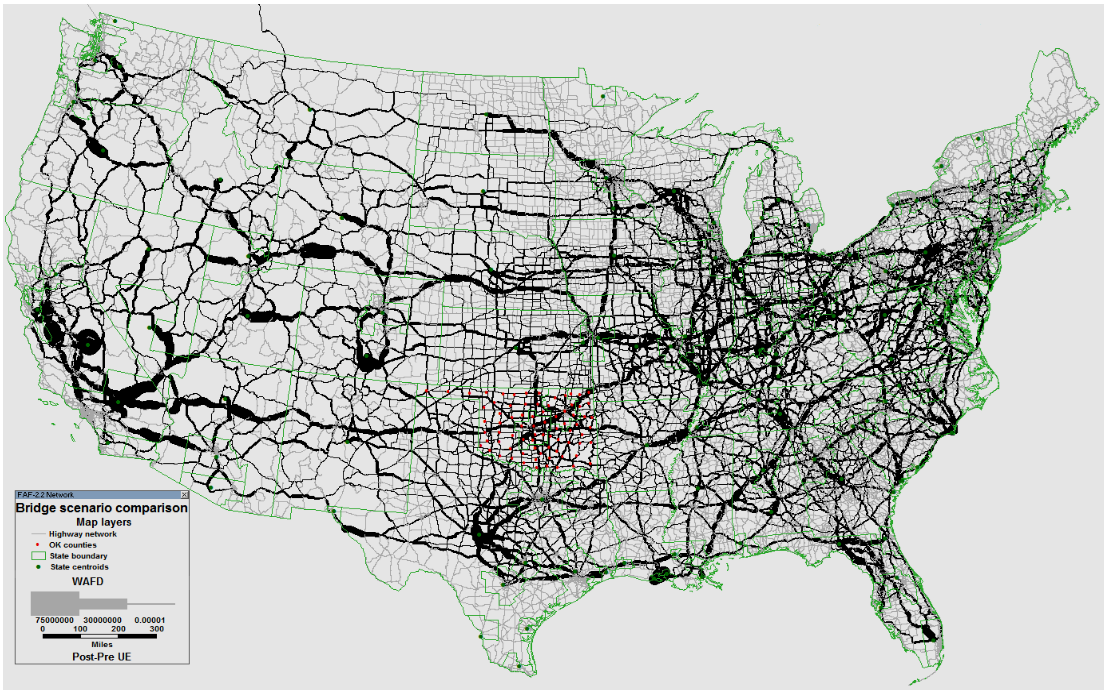

Figure 4.6: Post-pre WAFD, UE, U.S.

The results comparison with the VCR measure are given in the Table 4.3 according to the FCLASS and RUCODE attributes of the roadway network; positive change with green and negative change with red colors.

Table 4.3: Pre-Post Disaster VCR Changes, UE, FCLASS/RUCODE

FCLASS				
Congestion	**Interstate**	**Major Arterial**	**Minor Arterial**	**Others**
Under Capacity	0.40%	0.11%	-0.07%	-0.35%
Medium-Severe	-0.41%	-0.10%	0.07%	0.23%
Severe	0.01%	0.00%	0%	0.11%
Most Severe	0%	0%	0%	0%
RUCODE				
Congestion	**Urban**	**Small Urban**	**Small Urbanized**	**Large Urbanized**
Under Capacity	0.00%	-0.01%	0.00%	0.01%
Medium-Severe	-0.01%	0.01%	0.00%	-0.02%
Severe	0.00%	0%	0%	0.01%
Most Severe	0%	0%	0%	0%

In the post-disaster case other classified roads have increased medium-severe (0.23%) as well as severe congestion (0.11%), some parts (0.01%) of the interstate classified roads have severe congestion. According to the RUCODE attribute, the medium-severe congestion increased in small-urban area coded roads (0.01%), and severe congestion increased in large urbanized area coded roads (0.01%).

Approach I vs. Approach II, post-disaster comparison, UE

We compare the difference of the two approaches on the U.S. roadway network level in Table 4.2. Approach II results in a slightly higher level of severe congestion (2.79 % vs. 2.43%). The roadway network that is utilized under capacity is 82.88% in the second approach and 84.3% in the first approach. Distribution of the $T_{l,b}, T_{nb}$ on the U.S. network can be seen in Figure 4.6.

Comparison of results at the Oklahoma and the U.S. geographic levels show that VCR ratios are higher for the state roadway network, hence experience a higher congestion. Approach II show higher congestion compared to Approach I in general, since Approach I models a rather stabilized traffic conditions (informed users).

Flow Differences by State

We analyze the effect of the disaster on the freight flow by comparing the change in states. We compiled a list of the highest and lowest change by states, given in Table 4.4.

We can differentiate the effect on from, to, within, and through freight flows of a state. Because this particular disaster affects only the network, and as a result the within freight flow doesn't change, and the highest change is expected to be in the through freight flow movement. The reason behind this is for each state the amount of freight flow to and from this state doesn't change due to the disaster and continue to use this state's roadway network. In the case for through freight flow, the intermediate path selection can vary to minimize the cost, even though the freight originates and destined to the same pre-disaster OD pair. Hence, the change we observe in Table 4.4 is the through flow changes by states. According to the results OK lost 0.046% of its through freight flow because of the I-40 Bridge collapse. In addition, the freight flow increased on the roadways, such as at DC, LA, and AZ.

Table 4.4: Top 10 and bottom 10 of the total flow changes by state, UE.

Top 10		Bottom 10	
State	% of total flow change	State	% of total flow change
DC	0.14%	AR	-0.17%
LA	0.10%	UT	-0.07%
AZ	0.08%	FL	-0.05%
IL	0.08%	OK	-0.05%
MS	0.07%	CO	-0.04%
TX	0.06%	NV	-0.04%
GA	0.04%	TN	-0.03%
MN	0.03%	IA	-0.03%
IN	0.03%	AL	-0.02%
MO	0.03%	NE	-0.02%

4.6 Economic Impact Analysis

We develop a regression model to explain the effect of changing freight flows at state level. The effect of the I-40 Bridge collapse is defined using the relationship between the GSP and the total freight flow of a state. Total State Flow (TSF) is defined as the sum of freight flows on all links for each state, determined with the UE algorithm.

We assume the regression model holds for the post-disaster GSP values. The most representative model is $ln\ (GSP_s) = 4.1342 + 0.9016\ ln(TSF_s)$ with R^2 = 53.59%.

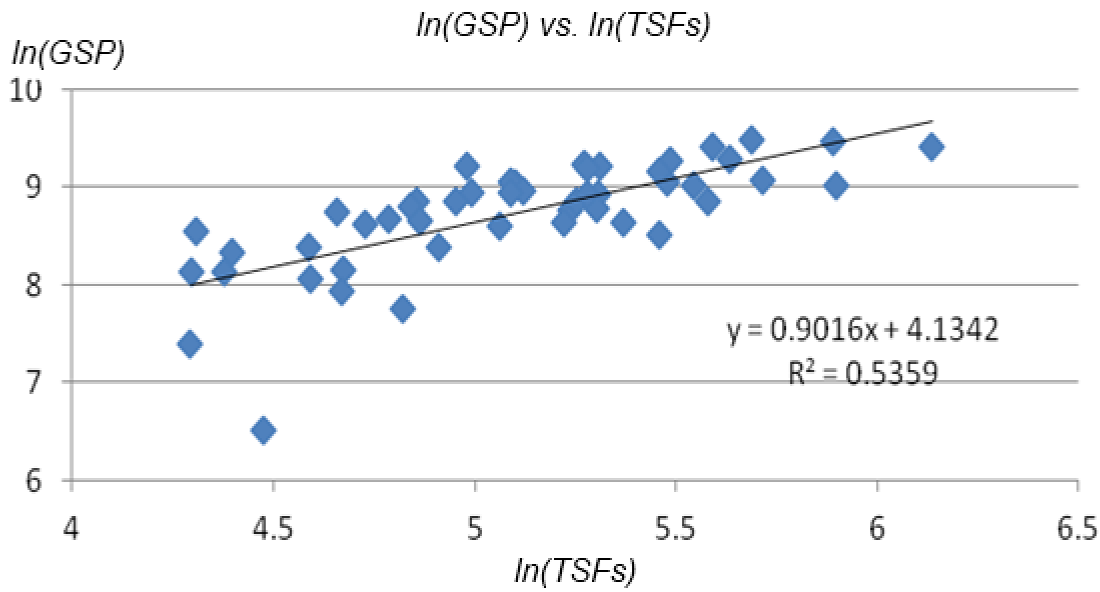

Figure 4.7: Log linear regression model of ln(GSP) vs. ln(TSFs).

The BTS data indicates the ton-mile cost for the year 2002 is 28.196 cents, and by state economic impact values are calculated and given in Table 4.5.

Table 4.5: Economic impact estimated with the BTS data.

State	Negative Impact ($millions)	State	Positive Impact ($millions)
AR	($41,554)	TX	$60,375
UT	($14,612)	GA	$24,171
FL	($13,528)	LA	$19,259
AL	($11,706)	MO	$17,134
CO	($9,656)	AZ	$10,372
TN	($8,068)	IN	$7,277
WI	($3,901)	KY	$5,521
NV	($3,442)	IL	$4,659
CA	($3,306)	OH	$3,800
MD	($1,069)	OK	$2,871

According to the regression model, AR is the most negatively impacted state, and TX is the most positively impacted state due to the bridge collapse.

4.7 Conclusions and Remarks

Extreme events, natural and man-made disasters, damage buildings and houses, as well as lifeline systems, such as the transportation system. Bridge collapses received attention in the last decade due to the frequent transportation network disruptions. The existing disaster impact research has been on the local impacts in social, demographic, or physical aspects using gravity models and local networks with little attention paid to the freight flow changes and impacts at the regional and national scopes.

We differentiate this study by using the U.S. highway network and common flow assignment models to determine the effects of a bridge collapse on the redistribution of freight flow at local, regional, and national levels.

We analyzed the collapse of I-40 Bridge, which took lives, interrupted the traffic flow, caused miles long traffic jams and economic loss. The results show that the disaster effect on the freight flow movement is high in the local roadway network, but other sections of the network are also affected. This shows that the distance from the disaster location may not be a key variable in measuring freight flow changes and impacts. Consequently, the gravity models, which consider the distance as a multiplier factor and operate on the assumption that the further away from the disaster center, the less flow changes and corresponding to fewer impacts. Even though this assumption maybe valid for local analysis, but not necessarily valid for regional and national impact analysis, since they show little distance relevance. Studies conducted by the Office of Freight Management and Operations under FHWA [2004] and Southworth, *et al*. for U.S. Army Cops of Engineers [2006] supports this conclusion.

As a result of the I-40 Bridge collapse, total freight flow in Oklahoma decreases. Similarly, the freight flow paths change and some states experience an increase while others experience a decrease in freight flows on their roadway networks. The freight flow change is observed both locally, regionally and nationally, whereas a distinct pattern is the east-west corridor along the major interstate highways. The local pattern in Oklahoma is spread over the state; however, this is due to our analysis of a much finer geographical level; 77 counties rather than 3 MSAs to represent the freight flow movement of Oklahoma. Parallel to the change in freight flow movement, the incurred cost, in terms of increased congestion and higher fuel consumption due to increased miles-traveled and time-traveled, is spread to various states. The highest cost impact is on the east-west corridor that corresponds to the largest changes. Depending on the extent of the disaster, such costs may need to be accounted in business decisions to minimize costs; for instance, to move to a new location instead of rebuilding at a disaster area or at a location where the business can be impacted. Transportation planners can consider the immediate effects of a bridge collapse, which is modeled by Approach I and II. Using Approach II for emergency re-routing analysis or preparation can be more effective.

In this research, we don't include a modal change or damages to other structures and the software program is more suitable for long-term analysis, which may underestimate the performance measures. Research opportunities exist in multiple dimensions, one of which is to use a finer geographic level data for the analysis. We can capture the disaster effect on freight flow at a finer level by using a finer geographic level than MSAs, such as counties. We use 77 counties to represent the state of

Oklahoma and 114 FAF MSAs to represent the rest of the U.S., which can also be represented at a finer level. Similarly, the economic impact analysis on disasters and infrastructure damages need to be studied at a detailed level, possibly using a spatial input-output model or cost-benefit analysis. Although there are several methodologies available for assessing economic impact, such as input-output model, applications and databases are rather limited for multi-levels disaggregated studies.

In the next chapter, we investigate the question of how we can compare extreme event impacts on freight across different disasters. We develop a framework to analyze the impact of an extreme event on freight movements that is illustrated with three extreme events. We further discuss extreme event impacts such as the freight demand and supply changes and the spatial and temporal aspects.

Chapter 5: A Framework to Analyze Extreme Events with Case Studies

The world rests on the assumption of systems working together in harmony to make our life easy. Theories have been developed for these systems, with the 'under normal conditions' assumption; which generally model a system independently, as a black box. This assumption is successful, except at times of extreme events. These extreme events challenge us with out-of-the ordinary conditions that we are generally not ready for. Hurricanes, earthquakes, bridge collapses, and other natural and man-made disasters, in short, extreme events, disrupt our routine. Research is crucial to understand unexpected circumstances, to manage discrepancy or to minimize, or to eliminate the disruptions of the unexpected events.

5.1 Introduction to Extreme Events and Freight

In the previous chapter we discussed how effects of an extreme event, a bridge collapse on freight movement could be analyzed. The scenario was composed of a single point in time and we analyzed the differences between the pre-disaster and post-disaster freight flow changes. However, most of the time the extreme events are more complicated, such as by involving more than one time interval and multiple disruptions on the network.

The 1994 Northridge Earthquake resulted in multiple failures on highways, each of which recovered at a different pace. The transportation related loss caused by the Northridge earthquake was estimated as $1.5 billion; 23% of the $6.5 billion business interruption loss was attributed to transportation (bridge collapses and highway) damage [Gordon, Richardson, and Davis, 1998].

The 2005 Hurricane Katrina damaged the highway network severely, mainly the bridges on I-10 and U.S.-90 highways. Padgett, *et al*. [2008] studied the damage patterns to bridges resulted from Hurricane Katrina and developed a relationship between storm surge elevations, damage level, and repair cost. They observed that the higher the storm surge the higher the damage was, although debris impact was a significant reason for damage. The authors highlighted the potential vulnerability of highway bridges to hurricane, storm surges, and how simple retrofit strategies, such as transverse shear keys, could help mitigate damage costs.

The research interest in this area increased in the recent years, especially after the Hurricanes Katrina and Rita. The inadequate goods transportation to the disaster regions prompted further research in emergency logistics and disaster response strategies. Haghani and Afshar [2009] developed a comprehensive model that describes integrated supply chain operations in response to natural disasters, as well as finding optimal locations for temporary facilities considering the capacity constraints. Definitely, fast and careful use of re-routing strategies help minimize the adverse results of extreme events. On more passenger flow at times of extreme events, Chin et al. [2006] showed a 10% improvement in average travel time for all travelers when only passenger vehicles are allowed and the trucks are kept on highways rather than diverting all vehicles to surface streets.

Major disruptions to transportation network lead to significant changes in freight flow and negative impacts on economy. Transportation disruptions result in congestion, closed roads, restricted lanes, which affect system users through trip cancellations, re-routing, or delays. For example, Papadakis [2006] reported a loss of about $178 billion due to the 1995 Kobe earthquake in Japan that is equivalent to 0.7 percent of global gross production.

Along with emergency re-routing, reconstruction of the disrupted transportation network is critical due to its vital role in the restoration of other lifelines (e.g., electricity, water, gas lines). Reconstruction strategies should consider possible traffic demand changes [Chang and Nojima, 1998] as well as the disrupted link properties, such as capacity, traffic volume, and spatial location, and overall transportation network redundancy [Wakabayashi and Kameda, 1992; Sohn, 2006; Basoz and Kiremidjian, 1995]. As our reliance on the transportation system increases, how can we prevent, mitigate and respond to extreme events, which threaten this very critical resource?

In order to prepare, mitigate, and respond to disruptions in transportation, we need to understand the behavior of transportation system in case of extreme events. In this chapter, we develop a framework to analyze the impact of an extreme event on all-commodity freight transport, and it is applied to different extreme events. It is demonstrated that the framework can be applied to any extreme event, at any geographic level by focusing on the affected section of the transportation network. Lastly, changes, such as supply-demand balance, re-routing, and repair strategies are discussed and then significance of the spatial distribution of freight transportation in U.S. is illustrated. The framework provides a straightforward and easy approach for analyzing the after-math of extreme events, hence benefitting transportation planners and decision makers in re-routing and restoration strategies.

5.2 Methodology

The developed framework is composed of relevant data: GIS network data analysis, traffic assignment, and analysis of the results with selected performance measures. The methodology is given in Figure 5.1. The transportation network (a roadway, railway, waterways, airways, or a multimodal network) and freight flow data (an OD matrix which has goods flow) are necessary for the analysis. As discussed in the previous chapters, freight data and transportation networks are available from FAF, NTAD, BTS, NHPN, and TIGER; most of them are free and can be downloaded from the Internet.

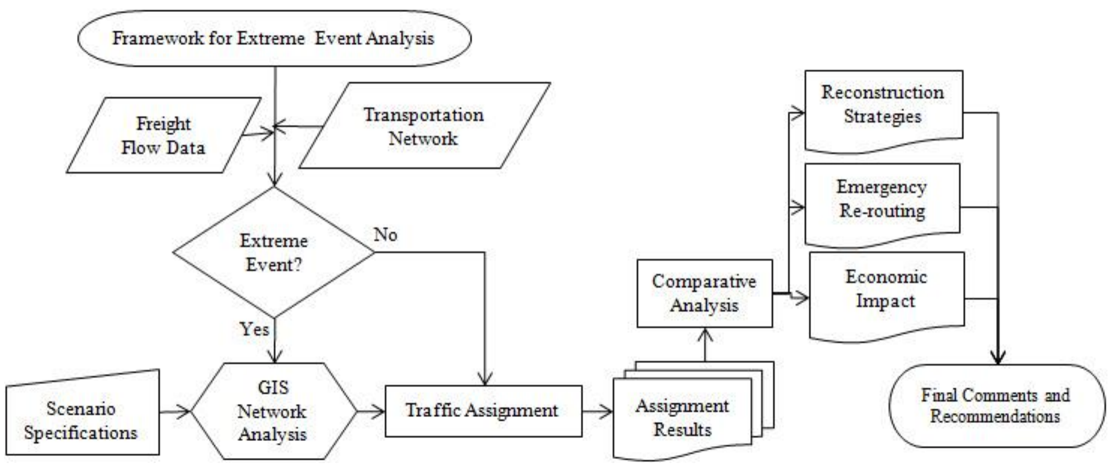

Figure 5.1: Framework to analyze disruptions on freight transportation.

Either a real or a hypothetical extreme event can be analyzed by defining scenario specifications. Scenario specifications are composed of the variables of interest in the analysis, such as extent of network infrastructure damage, time intervals, and spatial units (i.e. state, MSA, or county), and all or selected commodities/industries. The GIS network analysis step represents the network data as well as the OD matrix changes; for example, road capacity changes as inclusion, exclusion, selection of links or nodes, and supply-demand balance. From a network analysis point of view, extreme event changes on network infrastructure are grouped into 4 categories: node, link, area, and hybrid (which may include several links, nodes and/or areas). An earthquake may cripple the transportation network, which can be represented as broken link(s), damage a production facility that can be represented as a node removal (or removal of the node from the OD matrix), and a flood or a hurricane may result in one or more inaccessible areas including nodes and links, which referred here as a hybrid scenario. As in all transportation studies, the network is an important component of this study. A detailed network provides a more accurate traffic distribution, hence a better estimate of the short-term impact. When analyzing multiple time intervals, changes in scenario specifications should be prepared for each time interval.

A base line (pre-disaster) performance level analysis, determined with original network and freight data, is used for comparison and analysis. The traffic assignment step uses the transportation network information and the OD matrix to calculate the amount of freight flow that is transported by each link on the network using the transportation network and the freight data. AON, UE, or SUE assignment algorithms can be selected based on the assumptions of the user behavior; for instance, if route decision is based on distance or cost, AON or UE can be selected, respectively. TransCAD has built in algorithms for traffic assignment, or it can be coded using programming languages.

Assignment results are obtained by the traffic analysis step. Assignment results show the number of vehicles that utilize each road segment (link) of the network which then are used in the comparative analysis step to analyze the impact of the extreme event on the freight flow. Measures, such as VHT, VMT, VCR or other user-defined measures, can be calculated. VHT, VMT, and Volume over Capacity Ratio (VCR) measures consider given (or estimated) time, distance, and capacity of the transportation network; but they may not reflect on the network conditions, such as road conditions, terrain of roads unless these are built into network specifications (i.e. in the form of time, speed, or capacity).

One of the measures can be the *change in traffic flow* between scenarios; it is calculated as the pre- and post-freight flow difference per link. An increased VMT measure shows an increased usage of the corresponding link.

In addition, we can make use of the FCLASS and the Rural Urban Code (RUCODE) classification of the network provided by the FAF. These attributes provide the analyst an opportunity to analyze the scenario results with different perspectives.

These results can be used to plan for building emergency re-routing, construction and repair strategies, or economic impact estimations. The following short list provides some examples:

1. Post-event freight flow traffic, total freight change, and VCR help assess new traffic flow requirements, constraints, and new response methods to adjust to the new traffic flow pattern.
2. Increased VCR shows the bottleneck locations on the network used for defining reroutes.
3. Through flow differences indicate a possible freight flow behavior change.
4. The economic impact of the disaster on the freight transport can be evaluated by interpreting the freight flow changes with measures such as VHT and VMT and using tools such as cost-benefit analysis and multi-regional Input-Output (I-O) models.

Last step of the framework is where all the analysis results are combined and comprehended together to provide the complete understanding of the extent of the extreme event on the freight flow.

5.3 Illustrations of the Methodology

The roadway network and the freight flow data $FAF^{2.2}$ provided by FAF are used for the illustrations of the methodology. The transportation network has distance, capacity, FCLASS, and RUCODE attributes, which are utilized for performance measures. An OD matrix is prepared with the freight data of year 2002, and it is summarized for each origin and destination pair for all commodities. The following illustrations present the application of the framework starting with the scenario specifications and focus on the GIS network change implementations and how results can be used for re-routing strategies and priority repair strategies.

Economic impact estimation is not discussed here; it can be considered as a future research direction. The last step of the framework, final recommendations and suggestions, is discussed at the end of the chapter for all examples.

Extreme Event 1: Bridge Collapse

Bridges can be represented as a link or multiple links based on the network structure. In the data preparation, if the bridge is closed, the corresponding link can be removed from the network or its capacity attribute can be set to zero. If the bridge is partially closed, the link's capacity attribute can be decreased accordingly.

In case of a bridge collapse, traffic is re-routed. As a result the re-routed traffic travels longer distances, has increased travelling costs, and delay in deliveries. If the bridge is the only connection between an OD pair, then the freight data matrix can be modified since there cannot be any delivery between the OD pair.

Illustration 1: I-40 Bridge Collapse, OK, 2002

The I-40 bridge is a major east-west route with an estimated 20,000 vehicles/day in year 2002. The bridge collapsed after being hit by a barge on May 26, 2002. After the bridge collapse the traffic was re-routed; however, massive traffic congestion created up to 12-mile queues that subsided when the bridge partially reopened after 2 months, on July 29, 2002. After another six to eight weeks, when all lanes were opened, the traffic conditions returned to normal.

The *scenario specifications* includes the following:

- Network damage is modeled as a single link failure,
- Before and after the bridge collapse are the time intervals, and
- The national and local geographic levels of interest are OK and U.S., respectively.

At the *revisited GIS Network and Traffic Assignment* step, the network is modified; either the link is removed or its capacity is set to zero. Then the updated network is used in the traffic assignment step. AON and UE assignment models are applied. Total flow change, VHT, and VMT differences of pre- and post-disaster are derived using the traffic assignment results.

Comparative analysis of the results shows the changes at the bridge area (Figure 5.2). In addition to the bridge area, decreased flows (Figure 5.2, given in blue) on I-40 highway and increased flows (Figure 5.2, given in orange) on I-44 and I-35, and in other parts of the network are observed. Results indicate the bridge collapse not only changed the traffic flow for immediate network surrounding the bridge, but it is also changed for the surrounding region; even spreading to other states. These conclusions are also confirmed with the studies conducted by the Office of Freight Management and Operations [2004] and U.S. Army of Corps of Engineers (USACE) [2009].

The decrease in total number of trucks using the OK transportation network was 0.005%, and the VHT and VMT measures increased by 0.005% across U.S. A detailed look show that in all FCLASS categories there is an increase in the number of miles driven, and the major arterial coded roads are driven more.

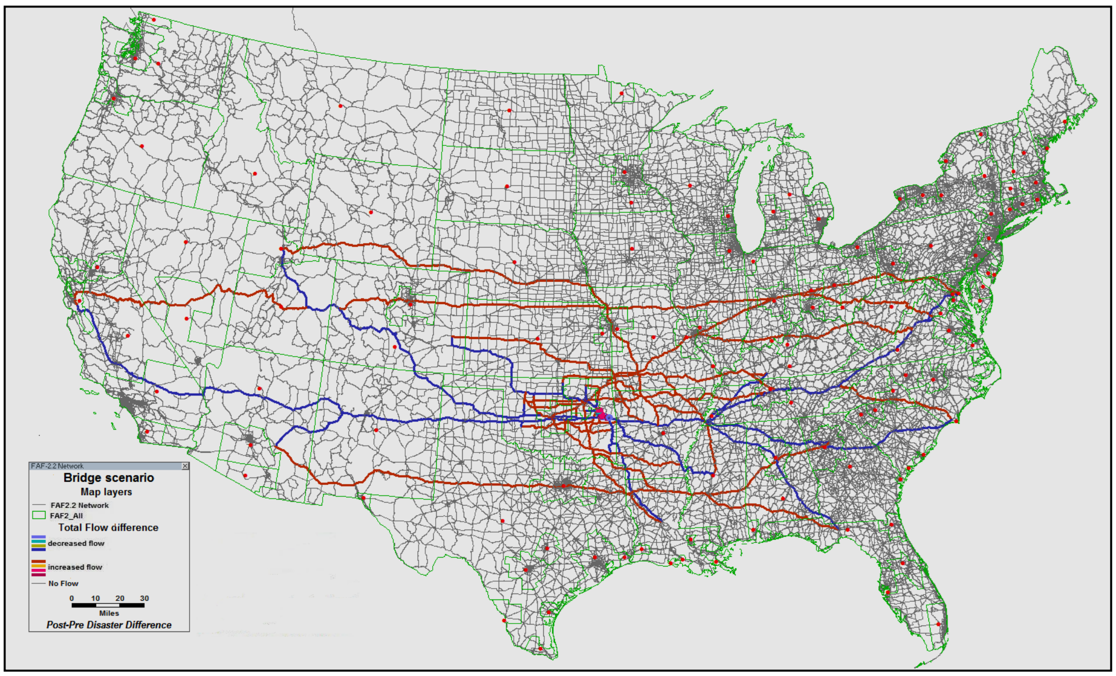

Figure 5.2: Bridge collapse example, AON.

For emergency re-routing, the results can be comprehended as such: the changes show that interstate roadways and major arterials are used under capacity, which implies that the freight traffic shifted to the minor arterials (both on U.S. and OK roadways). In this case, re-routing traffic and resources to other major arterials to minor arterials would relieve the traffic. The VHT and VMT increases guide in identifying the bottlenecks created by the bridge collapse; for instance, the freight flow shift from I-40 to the I-44 shown on Figure 5.2 can be redirected to other routes to relieve the increased traffic on I-44. Because there is only one link in this scenario, the reconstruction priority strategies section is excluded.

Extreme Event 2: Earthquake

Major earthquakes damage more than one section of the transportation network, and consequently can be modeled as multiple link failures. In the analysis of large transportation disruption, the level of detail would be correlated to the depth of the analysis. For instance, for re-routing opportunities, knowledge of the network as well as timely information on the network conditions, emergency rescue, and supply-demand balance are crucial.

Illustration 2: The Northridge Earthquake, LA, 1994

On January 17, 1994, the Northridge earthquake (6.8 magnitude) heavily damaged the transportation infrastructure in the Los Angeles, CA area. The earthquake crippled the transportation network at multiple locations: I-5 at Gavin Canyon, SR-118 Mission/Gothic avenues, I-5/S-14 interchange, and at I-10 Fairfax locations. Repairs to these locations took between one month and up to 10 months (for more details refer to DeBalsio et al., 2002). For this scenario, to capture the local changes, we focus on CA at the state level and the U.S.

The earthquake damaged multiple links, so this example is modeled as a multiple link failure. Based on the recovery time intervals of the damaged network, multiple scenarios are created to observe the network change over time. In total there are six scenarios, in which some links become fully functional (reach Full Capacity, FC) or partially functional (Half Capacity, HC). The timeline for the scenarios showing the FC links and HC links for the corresponding roadway sections is given in Figure 5.3.

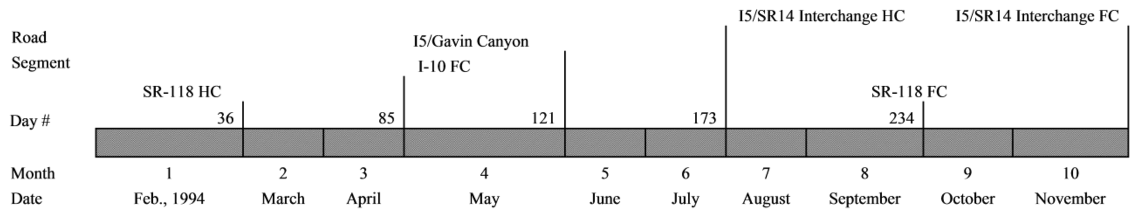

Figure 5.3 Timeline, Northridge earthquake damage recovery.

At the *Revisited GIS Network and Traffic Assignment* step, capacity changes to the damaged links are edited in the network properties (these links could be removed to indicate a full capacity loss, but since some of the links reach half capacity over time, we choose to make changes to the network properties instead). The updated network is used in the traffic assignment step, where AON and UE algorithms are applied.

In the *comparative analysis* step, the analysis of the results show that the VMT and VHT measures increase 0.02% and 0.06%, respectively. Scenario 1, all damaged roadway sections are under repair, VMT and VHT increases are higher than scenarios 2 (the SR-118 opens half-capacity for traffic), scenario 3 (I-10 opens all lanes), and scenario 4 (I-5 Gavin Canyon opens all lanes), but lower than scenarios 5(I-5/SR14 Interchange opens half-capacity) and 6 (SR-118 and I-5/sr-14 interchange open all lanes). Figure 5.4 compares the VMT changes between scenarios 3 and 5; where positive change is shown in green and negative with red. It shows the reconstructions of SR-118 and I-5/SR-14 is more significant than the others. In scenario 5, the difference between pre- and post-disaster VMT is low, but it is very high in Scenario 3. These differences are highlighted in the Figure 5.4; thickness shows the congestion for the corresponding scenario.

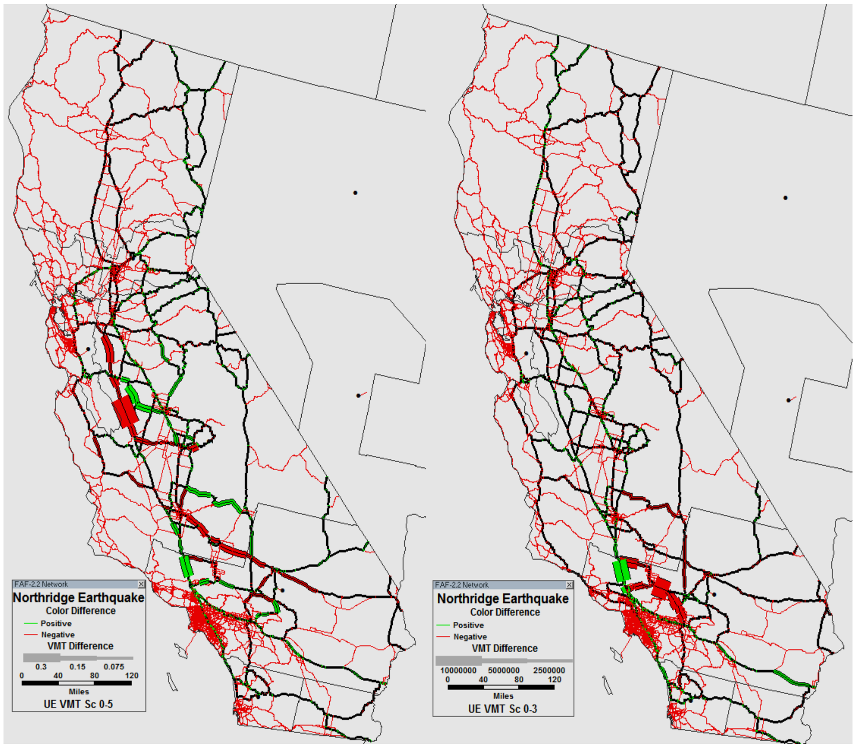

Figure 5.4: VMT increase (green), decrease (red), recovery, Northridge earthquake.

FCLASS and RUCODE changes are similar to the I-40 bridge collapse case. FCLASS categories experience an increase, mainly in major roads, then minor roads, and interstate category with the least increase. At RUCODE categories, rural area coded roads are driven more compared to the small-urban and small-urbanized area coded roads.

Extreme Event 3: Hurricane

Major hurricanes with high-speed winds and excessive rain fall generally result in multiple damages on the transportation network. Consequently, road sections may be under water, collapsed, or not functional. In addition, due to the hurricane, production facilities may halt production for various reasons, demand in the area may change; for instance, if the population is evacuated the demand for many commodities will be very low or none.

We model a hurricane as a combination of link failures and node failures, as a hybrid scenario. Similar to previous examples, the network damage can be addressed at the *Revised GIS Network Analysis* section, and the OD matrix can be updated according to the new supply-demand balance for the corresponding locations. Until the supply demand balance is reestablished, the OD pairs would face a decreased demand, if any.

Illustration 3: Hurricane Katrina, LA-AL-MS area, 2005

Hurricane Katrina, a category 5 hurricane, caused widespread damage in Louisiana (LA), Mississippi (MS), and Alabama (AL) (Figure 5.5).

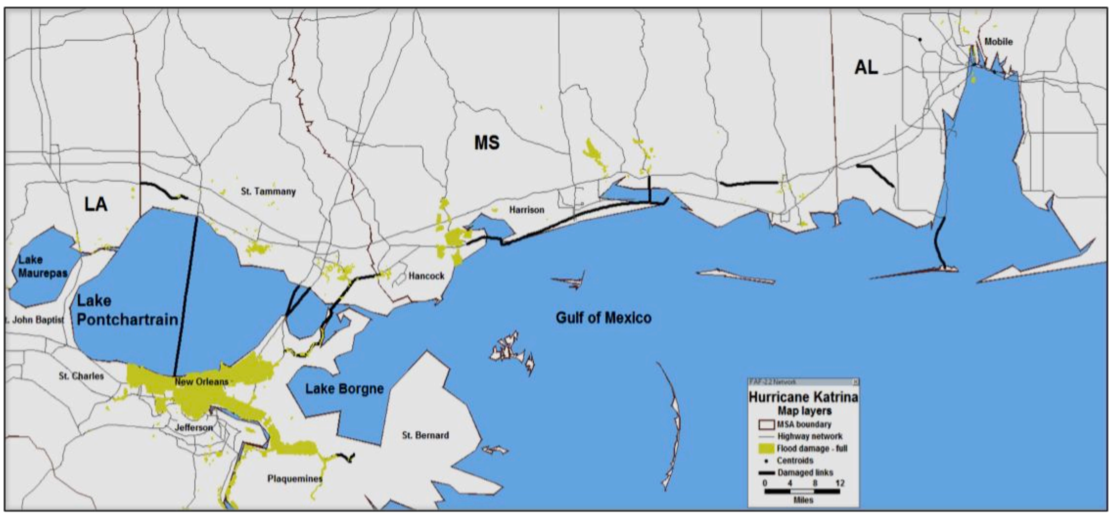

Figure 5.5: Hurricane Katrina, 3-state area.

Excessive landfall and high winds triggered massive destruction; homes, buildings, offices, and infrastructure were under water, damaged, or covered with debris (for more details on the details of the damage on the transportation infrastructure refer to DesRoches, 2006]. The flood data can be retrieved from the National Geospatial-Intelligence Agency (NGA) [2009]. This study utilizes the transportation network damage information and the flood data to construct multiple scenarios.

A baseline scenario is established with the network and data provided by FAF$^{2.2}$. Major damage on roadway network totaled 45 bridge and roadway sections [Padgett et al., 2009]. Twenty-four locations were selected based on the damage and the spatial location on the network (for more details on the extent of network the network damage refer to Padget et al., 2008). Scenarios are prepared based on the reconstruction schedule of the damaged network segments. The time line, recovery and the corresponding scenario are given in Table 5.1:

- Scenario 0.0 is the base line, pre-disaster conditions, no damage to the network.
- Scenario 1.0 is the first scenario after the hurricane makes landfall and damages the area; showing the conditions of 5 September 2005. The New Orleans area is flooded.
- Scenario 1.1 is the second scenario, showing the conditions of 21st of September 2005. The New Orleans area is flooded.
- Scenario 1.2 is the third scenario, where the network recovers from flooding, but none of the failed network segment groups are functional. The time stamp of this scenario is the end of the 1st month.

Table 5.1: HK Scenarios Time Line and Descriptions

			Bridges/Roadways conditions at the end of			
Scenario	Sept. 5th	Sept. 21st	1st month	3rd month	6th month	After 6 months
SC0.0	No flood	No flood	G1 Open	G2 Open	G3 Open	G4 Open
SC1.0	Flood I	*	G1 Closed	G2 Closed	G3 Closed	G4 Closed
SC1.1	*	Flood II	G1 Closed	G2 Closed	G3 Closed	G4 Closed
SC1.2	No flood	No flood	G1 Closed	G2 Closed	G3 Closed	G4 Closed
SC1.3	No flood	No flood	G1 Open	G2 Closed	G3 Closed	G4 Closed
SC1.4	No flood	No flood	G1 Open	G2 Open	G3 Closed	G4 Closed
SC1.5	No flood	No flood	G1 Open	G2 Open	G3 Open	G4 Closed

Note: starting with the first flood event ending on September 5, and second flood ending on September 21st, and grouping of roadways and bridges for the 6 month interval according to scenario number.

Scenario 1.3, 1.4, 1.5 are the rest of the scenarios, where the failed network groups recover, G1 at the end of 2nd month, G2 at the end of 3rd month, and G3 at the end of 6th

month, respectively. In scenario 1.5 the group G4 is still not functional at the end of the 6th month study interval.

At the *Revisited GIS Network and Traffic Assignment* step, the link, node, and area closured are implemented as given in Table 5.1. In Scenarios 1.0 and 1.1 the New Orleans area is flooded; therefore, we can either remove the corresponding area from the network, or the node representing New Orleans from the freight data matrix to indicate the node closure. For each scenario, closed (non-functional) link groups are excluded from the network; and when a certain group is open (functional), it is added back to the network. The framework is followed in the same fashion hereafter for the following sections.

At the comparative analysis section, total flow changes are highest in Scenarios 1.0 and 1.1 (the flood scenarios). The main reason for this is the supply-demand balance changes; the closure of the New Orleans area decreased the number of flows going out and coming in to the area. Corresponding VHT and VMT decreases are 0.78% (UE assignment) and 0.82% (AON assignment) for flood scenarios. Trading partners of the 3-state area are at the top in use of detours. In addition, the damage on I-10 and US-90 redirected the traffic to the parallel roads to the north.

The increased flows concentrate at the disaster regions and stretch up to Pennsylvania; for example, I-20, I-90, and I-10 South experience high traffic fluctuations. The supply-demand change in the New Orleans area causes the largest change in traffic conditions (Figure 5.6 top, blue lines indicate decrease, and orange indicate increase). Under UE assignment method, with the capacity consideration, the change in total flow on the network is widespread (Figure 5.6, bottom).

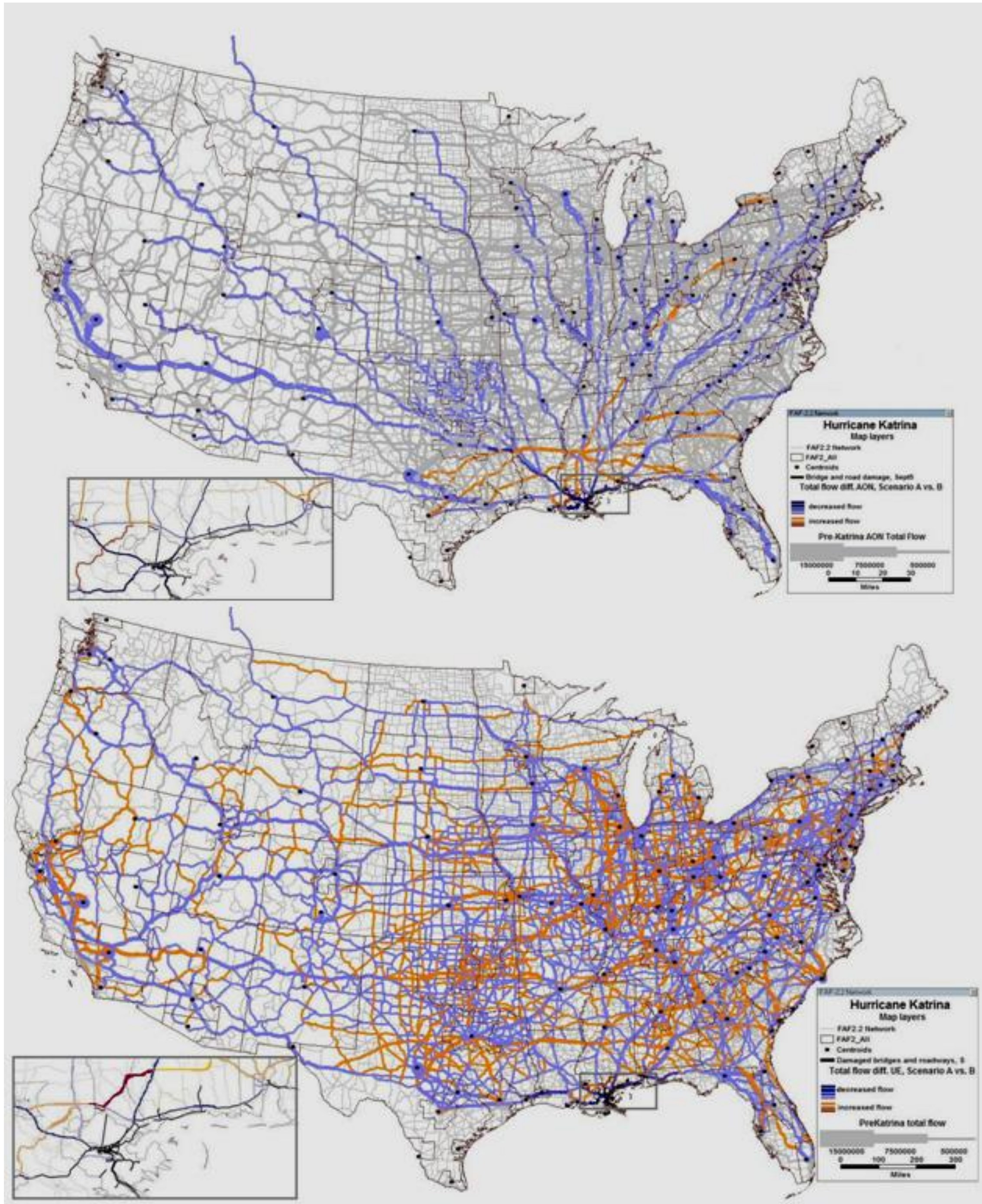

Figure 5.6: Total freight flow change in U.S., Hurricane Katrina, AON (top) and UE (bottom).

Increased flows are mostly observed on I-80, I-40, and I-75; whereas the decreased flows are mostly observed on I-10 and US-90 (as expected due to the extensive damage on the two highways). Scenario 1.2 shows an increase of 0.04% VHT and 0.06% VMT for UE assignment model, and these values decrease as the network recovers (Figure 5.6, bottom).

As time passes, the network is repaired; damage becomes more localized in the disaster region, particularly in the shortest distance case. Scenario performance differences are given in Table 5.2. We compare the results in the next section.

Table 5.2 : Comparison of results from the three extreme events.

	I-40 Bridge Collapse		Northridge Earthquake		Hurricane Katrina					
					AON			UE		
	AON	UE	AON	UE	Flood Scs	Dec-00	13/14-00	Flood Scs	Dec-00	13/14-00
VHT		0.01%		0.06%				-0.78%	0.04%	0.02%
VMT	0.01%	0.01%	0.00%	0.02%	-0.82%	0.05%	0.01%	-0.77%	0.06%	0.02%
FCLASS										
Interstates	+	+	+	+	---	---	--	---	---	---
Major Arterials	+++	+++	+++	+++	--	++	+++	--	++	++
Minor Arterials	++	++	++	++	+++	+++	++	+++	+++	+++
RUCODE										
Rural	+++	++++	++++	++++	---	+++	++++	---	++++	++++
Small-Urban	++++	+	+	+	-	++++	++	-	++	++
Small-Urbanized	+	+	+	+	--	---	++	--	--	++
Large-Urbanized	+	++	++	++	----	----	---	----	---	---

Note: VMT and VHT actual values are given, and for FCLASS and RUCODEs values are given as plus (+) and minus (–) signs, for increase and decrease comparison, respectively.

The recovery results in a continuous decrease of freight traffic, implying that the restoration/repair strategies benefit the freight movement as it decreased the VMT and VHT values. If the VMT or VHT or both had fluctuating values between scenarios, then changing the construction priority would benefit in decreasing the traffic congestion. Otherwise, a random repair selection may not provide the necessary relief.

The flood scenarios resulted in similar performance measure values, suggesting that the damage from the September 5th flood is similar to the flood on September 21st. Scenario 1.2, in which the region recovers from the flood and the supply-demand balance, we see the congestion level increase due to the damages on the network. Results of Scenarios 1.3 and 1.4 are very similar; congestion is higher than the base scenario (Scenario 0.0). Only after 6 months, Scenario 1.5, we see that the performance measures recover back to pre-disaster levels.

When we look at the FCLASS and RUCODE attributes, the freight movement changes in Scenarios 1.0 and 1.1 are higher than others. Traffic flow shifts from interstates and major roads to minor roads; the flow decreases in large-urbanized areas, increases at the rural areas.

Freight Flow Changes Compared: I-40 Bridge Collapse, Northridge Earthquake, and Hurricane Katrina

We applied the same framework to analyze impacts of different extreme events on freight flow. Even though the complexity of each scenario is different, only minor changes to the scenarios are needed to analyze the scenarios. In Table 5.2 the differences in performance measures of the scenarios, VHT and VMT, as well as the FCLASS and RUCODE increase and decrease between scenarios, are compared. FCLASS and RUCODE comparisons are given with +/- signs, indicating an increase/decrease, where number of signs indicates an absolute change. Here, not only the base scenarios, but also a comparison between scenarios and across examples can be done.

Based on the VMT and VHT dynamics of the examples, Hurricane Katrina is the one that causes the highest impact on the freight flow transportation, then the Northridge earthquake, and lastly I-40 Bridge collapse. The FCLASS behavior is similar in the I-40 Bridge collapse and Northridge earthquake examples; excess freight transportation shifts to major and minor arterials, decreasing the flow on interstates. In the Hurricane Katrina case, the freight transportation decreases on major and minor arterials, and mild increases are observed on minor arterials in Scenarios 1.0 and 1.1, the flood scenarios, (note that main factor is the change in supply-demand balance). In the rest of the scenarios of Hurricane Katrina, major arterials recover after the flood, while interstates continue to carry less flow. This result shows that the damages on I-10 and U.S.-90 are of critical importance.

The RUCODE comparison does not present a clear pattern when different extreme events are compared. We can mention that the rural-area coded roads carry more rerouted flow after extreme events, except in the case where supply-demand balance change that we implemented by removing the New Orleans area in the Hurricane Katrina case. Small-urbanized area coded roads are last to return to pre-disaster levels. In the Hurricane Katrina example, large-urbanized area coded roads have fewer flows in all six scenarios.

For each extreme event example we note the following:

1. Due to the I-40 Bridge collapse, the total freight flow transportation passing through OK decreased and shifted to other states' roadway networks. While some states had increased flows, others experienced a decrease. Overall flow changes are both regional and national, but the dominant spatial pattern is more apparent along east-west major interstate highway that stretches from CA to SC.

2. The Northridge earthquake example did not show a continuous decrease in the performance measures over time, which suggest a different repair strategy, might have a positive impact on freight flow. While CA experienced flow decreases, Nevada, Utah and Colorado experienced increased freight flow. Change in VMT is higher in CA, but also observed in TX, AR, and NV. The most positive impact on decreasing the VMT is established after the repair of the I-5/SR-14 interchange (which is a spatially critical linkage in the area).
3. Hurricane Katrina's impact on the freight flow pushed the traffic to the parallel north roadways, and trading partners of the 3-states region faced the largest decrease in flows.

The examples show that the I-40 Bridge is located on a critical east-west freight route and when it fails, the congestion and transportation costs increase, particularly on the I-70 and I-20 routes. Both Hurricane Katrina and the Northridge earthquake impacted coastal states. The damage of Hurricane Katrina is quantitatively higher and more widespread than the other examples. The freight flow shifted to the parallel roads to the north in the Hurricane Katrina example, and to the north and south in the I-40 Bridge collapse case; however, the direction of the shift is not clear in Northridge earthquake case.

According to FCLASS and RUCODE analysis, after the extreme events, in all FCLASS categories usage increases; highest in major arterials, and lowest increase on interstates (twice as much in major arterials). This suggests that the role of major arterials is important at the after-math of extreme events.

On the other hand, in the Hurricane Katrina case more flows shifted to minor arterials compared to the major arterials. The reason may be because of the extent of the event but this needs further investigation.

We can also make note of the following:

- Disaster regions inevitably face major changes after extreme events; in addition, other parts of the network may be impacted depending on the specifics of the event. As shown with the examples, the disaster area foci may not be a key variable in measuring the full impact of extreme events on freight flow on the national transportation network.
- Taking a system wide perspective (rather than a local perspective) in planning, mitigating and recovering from extreme events will benefit the total transportation system; i.e. measuring freight flow changes, bottleneck locations, and initiating recovery plans.
- The impact factor of an extreme event on freight transport is influenced by many variables, including but not limited to the following: network failures, network details, trading partners of the disaster region, attraction and production of the disaster region, the location of the disaster, performance measures, and assignment methods used in the analysis.

5.4 Conclusions and Future Research

Major extreme events impact the transportation system, and as a result critical freight disruptions occur. Recognizing this fact, this chapter explores the impact of extreme events on freight flow dynamics at local, regional, and national levels through development of a general framework. This research approach differentiates itself from the existing literature focused on gravity models, and their variants to model freight flow impacts in local networks. The developed framework is general enough to be applied on any extreme event, as illustrated for the I-40 Bridge collapse, Northridge earthquake, and Hurricane Katrina. The framework applied here utilized both traffic independent (distance) and traffic dependent (VHT, VMT, VCR) measures to capture freight flow changes and re-routing under different recovery strategies and scenarios.

GIS analysis of the transportation systems supports the spatial perspective of transportation systems. In the framework presented here, GIS network analysis is a critical piece, where the scenario specific information is built into the spatial network and data. Another important piece of information is the scenario specification. The details included in the network, i.e. network details and attributes provide opportunities for in depth analysis and unavailability of such information brings restrictions; the reliability of results depends on the quality and detail level of information. Analysis of impact over multiple time intervals enhances the results to provide timely action, for instance for recovery strategies. Selection of traffic assignment model, which is selected based on the user assumptions, influences the results, as shown in the illustrations. AON (shortest path) assignment model is useful in determining the emergency transportation routes, since emergency vehicles have the right of way and use shortest distance, as well as the restricted travel/transportation in case of extreme events. However, when such transportation limitations are lifted, transportation planners can use the real time network conditions to develop updated re-routing strategies by using the UE assignment model.

The developed framework illustrates that all extreme event impacts on the transportation network can be analyzed in a similar fashion: given scenario specifications along with publicly available network and freight flow data are sufficient for the application of the framework. Results are compared between scenarios, using user defined performance measures that enable dynamic comparison of recovery and reconstruction strategies.

In the next chapter, we discuss vulnerability of freight transportation systems, due to which the system fails. As the global economy relies heavily on the efficient movement of goods on interdependent multimodal systems, vulnerability of multimodal transportation systems presents the challenge to understand, prepare and recover from unexpected events. We focus on how to assess the vulnerability of a multimodal transportation system so that one can minimize the risk to the supply chain.

Chapter 6: Vulnerability of Freight Transportation

The research community first directed its attention to passenger transportation, then to freight transportation as businesses became global, supply and demand of goods shifted between regions, and, global economies started controlling local economies. For instance, Walmart, world's biggest retailer, is importing some 70 percent of its merchandise from China to sell in the U.S., buying 10% of all Chinese good production [Wang, 2013], which alone shows the influence of global economies.

Freight transportation plays a critical role in the global economy; for example, transporting scarce resources to other parts of the world satisfies demand for resources without a local supply. Freight transportation involves planning, scheduling over single and multiple transportation networks, multiple agents such as freight carriers. The inherent complexity and dynamic nature of these factors make freight transportation a highly complex multi-dimensional problem. Extreme events, natural or man-made, add another dimension of complexity. In order to maintain our quality of life, business, and ensure the proper functioning of the overall economy, a better understanding of freight and its behavior under normal and unusual conditions should be investigated.

In previous chapters we discussed the role of freight, its behavior under extreme events, how one can analyze, model, and determine the impact of an extreme event on freight movement. In this chapter we discuss the underlying reasons for these impacts, how one can define vulnerability in the freight movement context and how to quantify it. In order to do so, we present freight transportation in a larger scale and start with the so-called 'big picture' transportation system as a part of a larger system that is composed of various systems. The larger system, by design, is interdependent with the transportation system. We begin with examples of extreme conditions where the behavior of one system is affected by another system due to interdependency relationship. Next, we map out the layers of freight transportation systems focusing on multimodal networks. We discuss several characteristics of freight transportation, which are used to define vulnerability. We then use graph theory and multi-attribute theory to model and analyze vulnerability of freight movement, and lastly illustrate the methodology with a case study of the Hurricane Katrina of 2005.

6.1 Freight Transportation, a Systems Perspective

Freight transportation is a system that is dependent on other systems; likewise, there are systems, which depend the freight transportation. This interdependency is obvious when one of the systems fails; for instance, the interdependency between manufacturing and freight transportation. The floods of 2011 in Thailand caused various sectors to experience a slow down if not a halt in production. One such example is Toyota, which suspended production at its North American plants and halted other plants in Europe due to disrupted production plants in Thailand, and transportation due to the damage at the ports in Thailand. The Fukushima earthquake in April 2011, caused a nuclear plant failure resulting in a nuclear gas leak. The increased radiation levels made it impossible to sustain human life in the region for the foreseeable future (much like the 1986 Chernobyl Nuclear plant failure in Ukraine). The radiation clouds formed with the radiation leaked from the Fukushima nuclear plant travelled around the world increasing the radiation levels on its route. The tsunami, which resulted from the earthquake, destroyed the coastal areas and pushed debris islands across the ocean. The World Bank described this disaster as the costliest natural disaster in history with the physical loss being estimated from $235 billion to as much as $309 billion, the latter figure being nearly four times as much as the Hurricane Katrina ($81 billion) and almost equivalent to the GDP of Greece [World Bank, 2011; Nanto et al., 2011]. The actual costs of these disasters are expected to be higher due to the indirect damages.

Accounting for indirect damages and other losses is not straight forward. One well-researched example of an extreme event impact analysis of multiple systems is the 2003 Northeast blackout. The Northeast blackout affected about 50 million people in eight states in the U.S. and two provinces in Canada [North American Electric Reliability Corporation (NERC), 2004]. Loss of electricity resulted in other system failures; for instance, in New York City the water distribution and telecommunication systems failed, and the failure of the subway system stranded several thousand commuters in subways [Renesys Corporation 2004; NERC, 2004]. It was estimated that the blackout caused a $6.4 billion loss [Anderson and Geckil, 2003]. However, the initial event was a malfunction in a single electricity generation plant in Cleveland, Ohio, U.S.. However, the scale of this single malfunction turned into a multi-billion dollar disaster when several operating and planning violations were combined with a complex set of environmental and engineering conditions.

These examples show that the extent of the loss should be analyzed with a systems perspective to reveal the actual cost of extreme events. In the next section we first present a short summary of the previous work in transportation vulnerability, specifically in freight. We discuss freight transportation by mode and present a model for the multimodal freight transportation system with a systems perspective.

6.2 Freight Transportation Vulnerability

Transportation vulnerability has received attention particularly in security and critical infrastructure prevention research [Barnes et al., 2005; Hood et al., 2003; Lleras-Echeverri & Sanchez-Silva, 2001; Grubesic & Murray, 2006; Murray, 2011; DHS 2004]. Transportation vulnerability research evolved from the concentration of individual elements of transportation networks (local vulnerability) to group of links/nodes and network vulnerability (global/system-wide vulnerability) [Latora & Marchiori, 2005; Jenellius, 2006, Murray et al., 2008, Lleras-Echeverri & Sanchez-Silva, 2001] with single and multiple methodologies. For instance, graph theoretical concepts, such as closeness and betweenness [Latora & Marchiori, 2005; von Ferber et al, 2009; Sienkiewicz, & Holyst, 2005, Demsar et al., 2008], and Multi-Attribute Value Theory (MAVT) with GIS [Sivakumar and Batta 1994; Wijeratne et al. 1993; ReVelle et al. 1991; Chen et al., 2001; Delgado & Sendra, 2004] are used for assessing the vulnerability of transportation networks. However, there are relatively few studies taking advantage of multiple methodologies, e.g. MAVT and GIS (e.g. Zhang & Demsar, 2010; Dall'Asta et al., 2006) and even fewer studies on vulnerability of freight transportation (e.g. Dall'Asta et al., 2006).

Freight vulnerability research is a highly interdisciplinary field, involving areas such as geography, planning, transportation, environmental sciences and social sciences. Each discipline's definition of vulnerability, as well as the terminology used, may be different, overlapping, used interchangeably or as a complementary to other terms, such as with reliability or risk.

Reliability, Risk, and Vulnerability

Reliability is defined as "the ability of an *item* to perform a *required function*, under given *environmental and operational conditions* and for *a stated period of time*" [ISO 8402]. Here, the term *item* refers to any entity, which may be a component, a system, or a subsystem. A *required function* refers to any function that is required to be performed by the entity, which can be a single function or a combination of multiple functions. Therefore defining the functions of the entity is crucial for the reliability assessment. The environmental and operational conditions, as well as time dimension, set the expected/usual conditions and life cycle concepts within the definition. In relation to reliability (or unreliability), vulnerability is identified based on its diminished performance (in terms of capacity, time, cost, etc.).

More specifically, for transportation network reliability one of the earliest and simplest measures is terminal (connectivity) reliability which is the probability that there is still a connection between a pair of nodes in the network when one or more links are closed [Wakabayashi and Iida, 1992; Bell and Iida, 1997]. Other measures include travel time reliability, which is the probability that a trip will be completed within a specified time interval [Yang et al., 2000; Clark and Watling, 2005], and capacity reliability, the probability of accommodating a desired level of traffic for a given network [Yang et al., 2000; Chen et al., 2002]. Early contributions to the problem of finding the most vital link or node within networks include Garrison [1960], who used graph theoretical concepts, and Ratliff et al. [1975] and Ball et al. [1989], who contributed by developing algorithms.

Risk is defined as the result of a threat causing adverse effects to a vulnerable system (where threat is defined as the intent and capability; the motivation to harm, and, ability and capacity to attack a target and cause harm) [Haimes, 2006]. Risk is explained with a triplet of *scenario, frequency (probability)*, and *consequence of events* that may adversely diminish the system's ability to perform its mission [Kaplan and Garric, 1981]. As part of risk analysis, vulnerability of the system is identified for a specific scenario (a scenario approach). The calculation of a risk for a given scenario requires the knowledge of the probability of occurrence, level of impact on the performance of the system and the recovery capability of the system for this particular scenario.

While incorporated in reliability and risk, vulnerability doesn't yet have a widely accepted definition. The most common definition of vulnerability is the "susceptibility to injury or attack" [MW, 2008]. Other definitions of vulnerability include reduced accessibility, serviceability, and utility [Chen et al., 2007; D'Este and Taylor, 2003], which is defined within a social context, ability (of transportation system) to handle/survive threats [Asbjornslett, 1999] within the transportation infrastructure context, as well as probability and consequence of degradation [Nicholson and Du, 1994; Murray, 2011] with a risk perspective. These definitions show the multifaceted nature of vulnerability research due to the fact that vulnerability is context dependent.

Vulnerability of Freight Transportation: A Multi-Faceted Dynamic Attribute

In order to discuss what vulnerability of freight transportation is, we need to first define the freight transportation system. We use the roadway network here as an example, which we define as a two-layer system composed of a physical network layer and a service layer. In the case of multimodal systems, there exist multiple network and service layers that are connected via specified transfer nodes and edges (Figure 6.1).

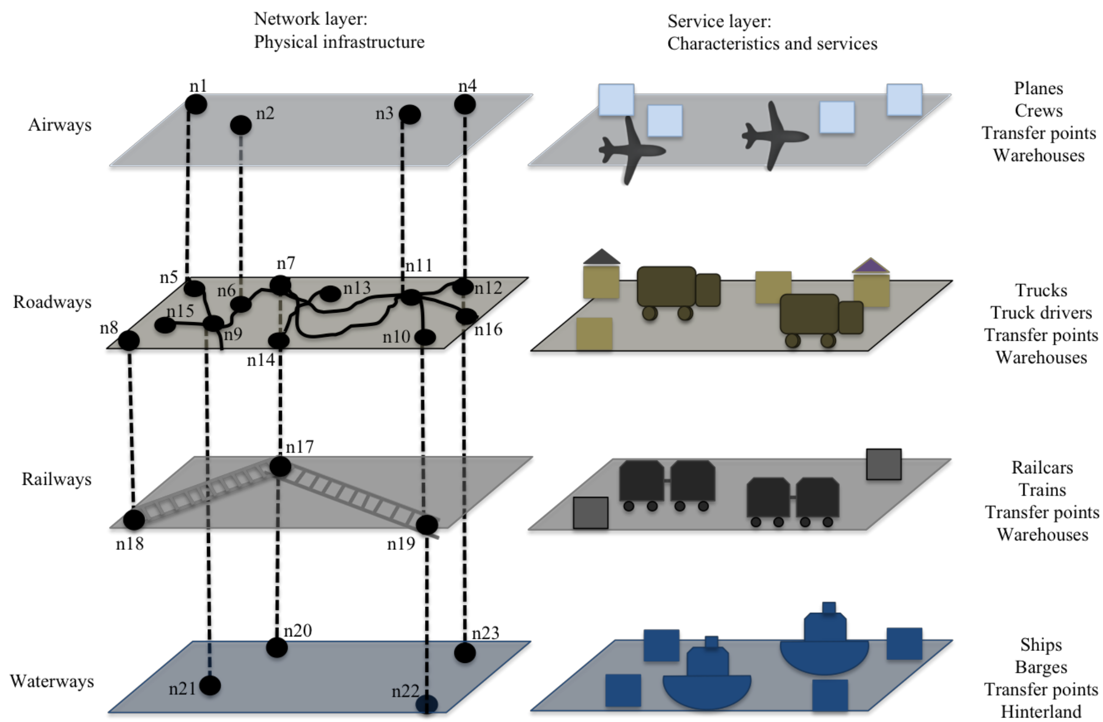

Figure 6.1: Network and service layers of the multimodal transportation system.

We define freight transportation vulnerability as a multi-faceted dynamic attribute that manifests itself as performance degradation at times of extreme events. Vulnerability of the freight transportation system is a direct or indirect result of the changes in (1) condition and decay, (2) capacity and use, (3) safeguards, (4) spatial conditions of the transportation system, (5) threats to the transportation system, (6) temporal aspects of the threat on the system, (7) policy and political conditions, (8) interdependency of the transportation system to the other systems [Grubesic et al. 2011], (9) network design, (10) demand to be satisfied by the transportation system, (11) transfer (of goods, personnel, vehicle, or storage) in case of multimodal transportation, (12) communication between entities in the systems, and (13) economic conditions (Figure 6.2). Each of these components influences vulnerability of the whole system.

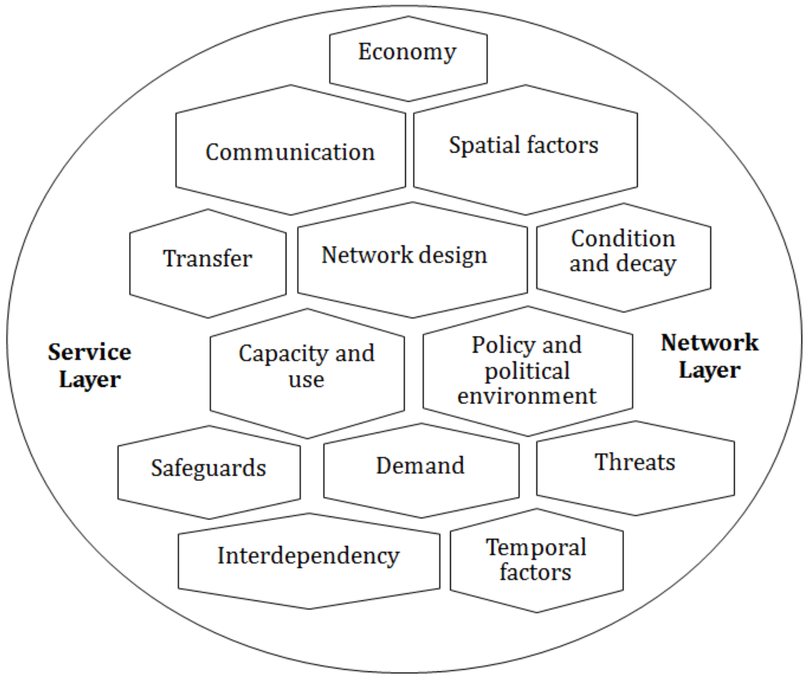

Figure 6.2: Dimensions of vulnerability, multimodal freight transportation systems.

The transportation system's functionality is dependent on the network design. For instance, hub and spoke networks are more susceptible to vulnerability than random networks due to the fact that when the spoke between the hub and a node is targeted, the spoke and the nodes connected to this spoke can easily be cut from the main network [Grubesic and Murray, 2007]. Similarly, the transfer nodes, which connect two or more transportation modes, play an important role in transportation. The supplier, the buyer and the freight company may be different, thereby making the communication between players even more significant for efficient and effective transportation.

Transportation systems, like other utility systems, require substantial investments and continuous maintenance, in addition to expansion where demand increases, all of which depend on the economy. Lack of investments, maintenance, or incomplete expansions increases the vulnerability of the transportation system to extreme events. Hence, the current condition (or the design condition) of the transportation system provides a baseline, which we assume not to be vulnerable within the design specifications. Network design includes safeguards and redundant components to compensate for some of the variation in traffic; however, it may not be sufficient for conditions experienced under extreme events. Temporal factors are generally significant; a bridge collapse at rush hour is certainly different than a collapse at 3 am. Similarly, the time it takes to repair the damage may influence the traffic long after the incident, particularly by changing travel patterns after major extreme events. This also shows the significance of how the demand on the transportation system affects the full impact of the extreme event.

The spatial component of the transportation system influences the movement of freight. For instance, soil and weather conditions affect the system functionality and may increase the vulnerability to certain extreme events, such as hurricanes and tropical storms at the Gulf Coast, tornados in Oklahoma, and, wildfires and earthquakes in southern California [Schmidtlein et al., 2008].

The transportation system is effected by disruptions to other systems, due to proximity and the interdependent relationship, such as in the 2003 Northeast blackout and after the 9/11 terrorist attacks where both passenger and freight transportation were impacted. Policies and the political environment play an important role in normal conditions, as well as under extreme circumstances, such as investment opportunities, mitigation and repairs after extreme events.

At times, sections of the transportation network become obsolete (such as when the repair of a bridge is costlier than building a new one, in which case the old bridge is closed and the new bridge is used); a section of the network becoming obsolete results increases vulnerability when there is demand for that section of the network; in other words, if this section is of no value in terms of demand, it doesn't change the vulnerability of the network.

In this chapter, unlike other definitions of vulnerability, we define vulnerability as the change in the various facets given in Figure 6.2. Let's assume each facet can be represented by a variable, x_i, where i corresponds to a facet, we can then define vulnerability of the system as follows:

$$Vulnerability = f(\Delta\, x_1, \Delta\, x_2, \ldots, \Delta\, x_{12}, \Delta\, x_{13}) \tag{6.1}$$

Since these facets also impact the functionality of the system, we assume that the vulnerability is projected as the change in system's functionality:

$$Vulnerability = (f_n - f_0) \tag{6.2}$$

where f_0 is the lowest system function value reached after an extreme event. In this study we assume that the system's functionality reaches state f_0 as a result of an extreme event. In general, the system may reach a level of f_k with a probability of p_k, and we can find the expected value of vulnerability, $E(Vulnerability)$:

$$E(Vulnerability) = f_n - \sum p_k f_k \tag{6.3}$$

Controlling these facets and reducing threats to the system will enable more efficient and effective transportation of goods by minimizing the vulnerability. In the following subsections we present a short background on vulnerability research and discuss the methodology.

Vulnerability Research in Literature

Early contributions to the study of transportation network vulnerability include Garrison [1960], who discusses elementary and descriptive use of graph theory to evaluate the effects of changes in transportation networks. Garrison concludes that network link failures could result in long detours. Algorithms are also developed to determine the most critical (important) links in the network.

With the increasing number of natural and man-made disasters, vulnerability research focused on the protection of critical infrastructure; however, methods used in transport reliability research were inadequate and new approaches and methods were necessary to assess the consequence of extreme events on the transportation systems [Berdica, 2002; D'Este and Taylor, 2003; Nicholson, 2003].

In recent studies various approaches and assumptions are studied in vulnerability research. For instance, Jenelius et al. [2006] calculated impact of the event based on the travel time change with and without the link closures given the volume of traffic. A game theoretic approach, where an "evil entity" deteriorates a link to maximize travel time and users choose detours to minimize travel time, is suggested by Bell [2000]. To simulate the traffic, congestion should be included in the estimations. However, capacity restrictions increase the complexity of the problem when the network is large. Consequently, most of the literature focuses on single link failures, whereas the reality is multiple links might be damaged because of an extreme event. Szeto et al. [2007] extended Bell's risk averseness approach [Bell, 2000] to consider multiple link degradation, and Kurauchi et al. [2009] applied the sensitivity approximation approach for calculating a new equilibrium situation to reduce computational time. Matisziw and Murray [2009] identified vital infrastructure without requiring complete enumeration by identifying bounds on the performance measures. Knoop et al. [2008] compared network robustness indices and concluded that different criteria may indicate different critical links. Therefore, the selection of performance measures is critical.

The primary approaches used in network vulnerability analysis are scenario-specific, strategy-specific, simulation, and mathematical modeling [Murray et al., 2008]. Scenario-specific approaches identify the most important scenarios in order to develop strategic plans for reducing associated vulnerability to disruption. Strategy-specific approaches begin with a hypothesized sequence or strategy of disruption. The goal of simulation-based analysis is to evaluate relatively large sets of scenarios to attain a realistic range of possible impacts. Mathematical models are used to identify the scenarios with the highest potential to impair the transportation system. However, each of these approaches has limitations, and integration of these methodologies provide knowledge to understand vulnerabilities of systems. The literature lacks comparison of various tools, models and applications.

In the context of freight transportation, we define the variations of the designed performance from the current performance as the vulnerability of the freight transportation system. The ability of the transportation system to handle these fluctuations is considered to be the freight transportation reliability.

We arrive at the research question of how to identify the vulnerability of the freight transportation system. Therefore, a detailed analysis of the appropriate models, performance measures and vulnerability criteria should be studied.

The next section provides the background for the methodology that we have developed to analyze vulnerability across the freight transportation network.

6.3 Methodology Background

One of the methodologies we use is the Multi-Attribute Value Theory (MAVT), which is a Multi-Criteria Decision Analysis (MCDA) methodology based on *deterministic* evaluations of alternatives as well as comparison and selection of an alternative. The uncertainty component is considered in Multi-attribute Utility Theory (MAUT) by introducing probability distributions instead of deterministic values. However, an adequate probability distribution may not be identified or the probability distributions may lead to inconsistencies in results. Simply stated, MAVT ignores the uncertainty and presents variables as static components, while MAUT explicitly considers uncertainty, but raises complications due to probability function assessment and dependent attributes within alternatives.

The second methodology is graph theory, a systematic approach that helps identify attributes, and is used widely in social sciences to determine the relationships between agents (i.e. individuals, groups). In this research the freight attraction and production locations as well as the relationship between the two are of importance. We investigate the degree, the cut vertices, closeness, and betweenness attributes for the $FAF^{2.2}$ U.S. roadway network.

Synthesizing graph theoretical measures and MAVT in modeling vulnerability of the transportation system enables us to account for both the network's physical and service attributes. We use graph theory to determine vulnerable vertices that play a significant role in freight transportation, such that the lack of these vertices may hinder freight transportation by means of time and distance. In addition, with the help of the visualization tool TransCAD, the value or the contribution of attributes, as well as their interrelations, are presented. Therefore, this research builds an integrative model that identifies critical locations to be used in strategic decision-making in freight transportation.

In the following sections we give a short background to both methodologies and build the integrated model, providing a short case study to illustrate this integrated methodology.

Graph Theory

Consider a *network model* representation of a freight transport system via a graph $G = \{V, E\}$, consisting of a set of vertices V and a set of edges (links) E. $|V| = v$ denotes the number of nodes while number of links is $|E| = m$. For this network we define the following measures: centrality, degree, closeness, cut vertex, betweenness, and, clustering coefficient.

Centrality measures describe the structural importance in a graph – vertices with higher centrality have a larger impact on other vertices. Three commonly used centrality measures are degree, closeness and betweenness. These measures were first introduced by Freeman [1979] in social network analysis.

The *Degree* of a vertex v, $\deg(v)$, is defined as the number of edges with v as an end-vertex, where $v \in V$. If the network is a directed network, we can also define *indegree* of vertex v, $\text{indeg}(v)$, as the number of edges with v as the terminal vertex (an end-vertex is both initial and terminal), and *outdegree* of vertex v, $\text{outdeg}(v)$, as the number of edges with v the as initial (originating) vertex.

$$\sum_{v \in V} indegree(v) + \sum_{v \in V} outdegree(v) = \sum_{v \in V} degree(v) \qquad (6.4)$$

The degree distribution, $P(k)$, of a network is defined as the ratio of vertices in the network with degree k. Therefore, if there are $|V|$ vertices in a network and v_k of them have degree k, then $P(k) = v_k/|V|$.

A graph is *connected* (or *vertex-connected or* called a *complete graph*) if every two vertices of the graph are connected. Obviously not every graph is connected, but every graph consists of connected components, which are called the maximal connected subgraphs of G.

A vertex is a *cut vertex* (also called an *articulation vertex*) if its deletion increases the number of connected components in a graph. A set of vertices whose removal turns a connected graph G into an unconnected graph is a *cut* (or a *vertex-cut*). Vertex connectivity, κ(G), of a graph G is the size of the smallest vertex cut. Vertex connectivity is usually referred to as *connectivity*. A graph is k*-connected* if its connectivity is equal to k. Similar definitions can be given for the edges of a graph. An edge is a *bridge* if its deletion increases the number of connected components in a graph. An *edge cut* of a graph G is a set of edges whose removal causes the graph to become disconnected. The *edge-connectivity* $\kappa'(G)$ is the size of the smallest edge-cut. A graph is *k-edge-connected* if its edge connectivity is greater than or equal to *k*.

The *closeness* of a vertex v, $cl(v)$, is the sum of the shortest distances from v to all other vertices. Closeness and degree are radial measures as they assess properties that emanate from a given vertex. Centrality of a given vertex in the graph can also be described by a measure based on the number of paths that pass through it. This measure is *betweenness*, $b(v)$, which is defined as the proportion of the shortest paths between every pair of vertices that pass through the given vertex v:

$$b(v) = \sum \frac{\sigma_v(s,t)}{\sigma(s,t)} \text{ , } for \, \forall \, v, s, t \, \in V \; and, v \neq s \; or \; t \tag{6.5}$$

where s and t are two distinct vertices of G, different than v, and $\sigma_v(s,t)$ is the number of shortest paths from s to t that pass through v (there can exist several completely or partially parallel shortest paths from s to t that are of the same length), and $\sigma(s,t)$ is the total number of shortest paths from s to t. Vertices with the highest betweenness are those that are located on many shortest paths between other vertices: the higher the number of shortest paths the node is on, the higher the node's betweenness is; hence, the higher the number of crippled shortest paths if the vertex is removed.

Girvan and Newman [2003] proposed an equivalent definition of betweenness for edges, *edge-betweenness*, which is defined as the proportion of the shortest paths between each pair of vertices that pass through the given edge e.

The clustering coefficient of a vertex v, $cc(v)$, is the measure of the vertex's importance in its immediate neighborhood (the group of vertices that are connected to vertex v, and the connections between each of these vertices in this group). Clustering coefficient is defined as the number of edges between the vertex v and the vertices within the immediate neighborhood of vertex v, divided by the number of all possible edges between them. More precisely:

$$cc(v) = \frac{e(v)}{\binom{d(v)}{2}} = \frac{2 \cdot e(v)}{d(v) \cdot (d(v)-1)} \tag{6.6}$$

where $e(v)$ is the number of edges between neighbors of v, and $d(v)$ is the degree of vertex v (the expression $\binom{d(v)}{2} = d(v) \cdot \frac{d(v)-1}{2}$ is the total number of possible connected vertices of size 2 which equals the number of all possible edges between the vertex v and its neighbors. Simply, an edge is selected arbitrarily from two different neighbors of vertex v). $cc(v)$ shows how tightly connected the node v to its neighbors is, 0 indicating a completely disconnected node and 1 indicating that it is fully connected to its neighboring vertices.

Multi Attribute Value Theory

In MAVT, one needs to first define the relevant attributes of the problem thus establishing the boundaries of the problem [Comes et al, 2009]. These attributes present the problem's overall objective, which can then be broken down into criteria and attribute performance measures [Comes et al, 2009]. A value function should be created for each attribute, which is then used for evaluation of the attribute. The value functions indicate the relative desirability of the consequence [Winterfeldt, 1986]. Finally, all the criteria are aggregated to form an overall assessment score, which is compared to other alternatives' overall assessment scores to make a selection among alternatives. There are various ways to form an overall assessment score, and this is called the aggregation problem. Multicriteria aggregation procedures (MCAP) provide solutions involving [Roy, 2005]:

a. Inter-criteria parameters such as weights, scaling constants, aspiration or rejection levels to define the particular role of each attribute in relation to other attributes,

b. An aggregation logic that accounts for the dependencies between attributes and the conditions under which a decision maker will accept or reject the performance of an alternative.

The most traditional approach is to use a synthesizing criterion. Generally, it is a mathematical formula that explicitly provides a unique criterion to synthesize attributes [Roy, 2005]. Multi-Attribute Utility Theory (MAUT), Simple Multi-Attribute Rating Technique (SMART), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH), and Analytic Hierarchy Process (AHP) are some examples of this approach (for further details, Figueira et al, 2005 chapters 7-10).

Estimating weights

Weights can be estimated using different methods, for instance, direct rating methods such as Simple Additive Weighting (SAW) or SMART (a decision maker assigns 10 points to the least important criteria). In the SWING [von Winterfeld and Edwards, 1986] method, a decision maker assigns 100 to the most important attribute and gives less to others with the results being normalized. The SMARTS method combines SMART and SWING. AHP is based on paired comparisons and the use of ratio scales in preference judgments. Ordinal weighting methods include rank-sum weights method, rank reciprocal method, centroid weight method, and rank exponent weights method. In ordinal weighting methods, DM is only asked to provide importance ranking of the given attributes.

Overall value function

An additive, multiplicative, or a linear value function can be generated, which then is used to compare alternatives. The additive model accounts for the complete set of attributes of each alternative and uses the regular arithmetical operations of a multiplication comparable attribute; hence, the attribute values must be both numerical and comparable. In an additive model the attribute (and all of their subsets) must be mutually independent. In a multi-linear model the strengths of preferences in any single attribute are not affected by constant values in other attributes [Winterfeldt, 1986].

Multi-attribute value theory is used to deliver a more accurate vulnerability value for the network junctions (nodes/vertices) within the network. An overall value is used to compute the vulnerability of each junction to provide guidance such as when making long-term decisions or strategic planning of transportation investment, or route (i.e. freight specific) analysis.

In determination of critical links, each junction can be considered as an alternative, a possible critical link. A higher overall value of a vertex indicates that it is more vulnerable. This individual vertex level can be considered as a local view. We can also define a global vulnerability for the network (system) in that case by considering a group of links, e.g. within an MSA, or, a state.

We defined various attributes in the previous sections. In the following section, we will discuss the attributes, objective function, and alternatives that we selected. We should note that different scenarios/alternatives may require different attributes; for example, a governmental perspective and an individual's approach to vulnerability would include some similar but also some different attributes; while the government focuses on the total system vulnerability (a global view), an individual user focuses on user specific route vulnerability (a local view). Here we will give a short overview of the different methods from Zarghami and Szidarovsky [2011], which can be found in any introductory MAVT book.

Simple Additive Weighting (SAW)

This method uses the relative importance of attributes assessed by the decision maker. Let w_i denotes the importance of attribute $i \in n$, where n is the set of attributes. We assume $w_i > 0$ and $\sum_{i=1}^{n} w_i = 1$. Then the overall value function, F_j is defined as a weighted average of the evaluation values with respect to the different attributes

$$F_j = \sum_{i=1}^{n} w_i a_{ij} \tag{6.8}$$

where a_{ij} is the outcome of the attribute i for alternative j, $j = 1,2,..,J$, where J is the set of alternatives. SAW requires normalization to overcome problems like unit differences. A simple linear transformation can be used to do so:

$$\bar{a}_{ij} = \frac{a_{ij} - m_i}{M_i - m_i} \tag{6.9}$$

where m_i and $M_i$are computed minimum and maximum values of attribute i.

The Analytical Hierarchy Process (AHP)

In this technique, weights of the attributes are assessed with pair-wise comparisons. Each pair of attributes is compared individually, independent of other attributes, or other attributes' contributions. Schema given in Table 6.1 can serve this purpose. Although pairwise comparisons are easier than comparing multiple alternatives at once, the resulting answers may not be consistent when all alternatives are considered. This is because we omit the relation between alternatives.

Table 6.1: The fundamental scale for making judgments.

1	Equal
2	Between Equal and Moderate
3	Moderate
4	Between Moderate and Strong
5	Strong
6	Between Strong and Very Strong
7	Very Strong
8	Between Very Strong and Extreme
9	Extreme

Note: Decimal judgments, such as 3.5, are allowed for fine tuning, and judgments greater than 9 may be entered, though it is suggested that they be avoided. Adopted from Saaty, 2005.

If the assessment is consistent, then the following relations should be satisfied:

(i) $\propto_{ij} = \frac{1}{\propto_{ji}}$, for $\forall\ i, j$, since $\propto_{ij} = \frac{w_i}{w_j} = \frac{1}{\frac{w_j}{w_i}} = \frac{1}{\propto_{ji}}$

(ii) $\propto_{ij} \cdot \propto_{jk} = \propto_{ik}$ for $\forall\ i, j, k$, since $\propto_{ij} \cdot \propto_{jk} = \frac{w_i}{w_j} \cdot \frac{w_j}{w_k} = \frac{w_i}{w_k} = \propto_{ik}$

Assuming the decision maker consistently assesses the weights, the weight matrix $A = \propto_{ij}$satisfies the following relation:

$$A\begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ \vdots \\ w_n \end{pmatrix} = \begin{bmatrix} \frac{w_1}{w_1} & \cdots & \frac{w_1}{w_n} \\ \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \cdots & \frac{w_n}{w_n} \end{bmatrix}\begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ \vdots \\ w_n \end{pmatrix} = n\begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ \vdots \\ w_n \end{pmatrix}$$

And using $w = (w_1, w_2, \ldots, w_n)^T$ then

$$Aw = nw$$

Meaning that n is an eigenvalue of matrix A with the associated eigenvector w. Matrix A is nonnegative and its rank is unity, since row k of the matrix is the w_k/w_1 multiple of the first row. As a result, there is one positive eigenvalue and all others have a value of zero. According to the Perron-Frobenius theory, n is the principal eigenvalue of A

and vector w is unique except with a constant multiplies. This vector can be normalized by dividing each component by the vector sum as in the following equation:

$$\overline{w}_i = \frac{w_i}{\sum_{j=1}^{n} w_j}$$

where $\overline{w}_i$ is the normalized weight of the ith attribute.

A good approximation to this weight can be obtained by computing the eigenvalues for calculating the weights. Sum of the elements of the different columns are:

$$\frac{\sum_{l=1}^{n} w_l}{w_1}, \frac{\sum_{l=1}^{n} w_l}{w_2}, \dots, \frac{\sum_{l=1}^{n} w_l}{w_n}$$

and by dividing each column by the sum of its elements the modified weight matrix A becomes:

$$\begin{pmatrix} \overline{w}_1 & \overline{w}_1 & \dots & \overline{w}_1 \\ \overline{w}_2 & \overline{w}_2 & \dots & \overline{w}_2 \\ \vdots & \vdots & & \vdots \\ \overline{w}_n & \overline{w}_n & \dots & \overline{w}_n \end{pmatrix}$$

which has identical columns.

However, if weights assigned by the decision maker are inconsistent, then the weight matrix will not have identical columns. Then, the best overall approximation column vector should be identified. Generally a simple algebraic average of the columns is used.

While pair-wise comparisons are easier to comprehend and decide, the decision maker may make an inconsistent decision. Therefore, we we calculate an inconsistency level for the decision maker to avoid such inconsistencies. In order to do so, a good approximation of the principal eigenvalue of the weight matrix A should be calculated. This value is different than the theoretical value n due to the inconsistency. The true principal eigenvalue n_e is calculated by multiplying each element of the normalized weight vector w by the corresponding column sum of the true comparison matrix and adding these products:

$$\sum_{l=1}^{n} w_l \cdot \frac{\sum_{i=1}^{n} w_i}{w_l} = n_e$$

A good approximation λ_{max} based on the approximating comparison matrix in a similar manner is:

$$ICI = \frac{\lambda_{max} - n}{(n-1)RI}$$

where ICI is the inconsistency index, and RI is the Random Index that depends on the problem size [Zarghami and Szidarovszky, 2011]

The procedure for AHP can be summarized as follows:

1. Construct weight matrix A using the pair-wise comparison of attributes,
2. Normalize each column of matrix A,
3. Compute the algebraic average of the columns of the normalized matrix for weights.

6.4 Preliminary Analysis

Graph Theoretical Measures

We transformed the FAF network is transformed into a directional network from a unidirectional network, and removed the U-turn information. The resulting network can be represented as $G = \{V, E\}$where $v \in V, |V| = 135{,}589$ vertices and $e \in E, |E| = 341{,}400$ edges. Since $v \ll e^2$, the network can be referred as a *sparse network*.

Degree Distribution

The degree distribution tells us that each node has at least a degree (indegree + outdegree) of 2, a maximum degree of 12, and has on average a degree of 5 (Figure 6.3 and Table 6.2).

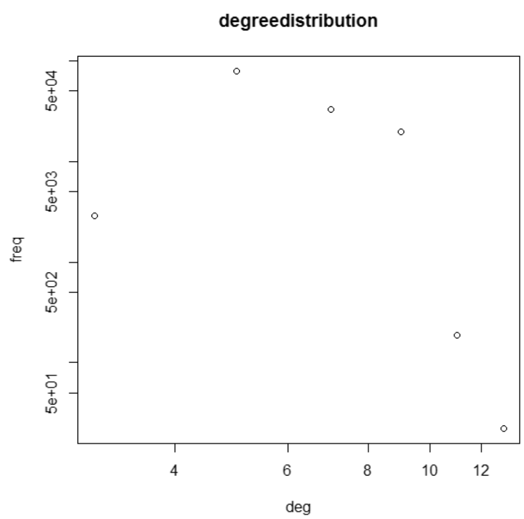

Figure 6.3: Degree distribution of roadway network.

Table 6.2: Degree analysis of roadway network.

Degree	
Mean	5.0358067
Standard Error	0.0041772
Median	4
Mode	4
Standard Deviation	1.5381375
Sample Variance	2.3658669
Kurtosis	-0.3067807
Skewness	0.8163703
Range	10
Minimum	2
Maximum	12

Real-life networks are usually not random, and we observe the roadway network is right-skewed (0.82), meaning that a large majority of nodes have low degree but a small number, denoted as "hubs," have high degree.

The color-coded vertex degrees can be observed in Figure 6.4. We can somewhat see it matching the national highway system (Figure 6.5), and the so-called hubs; however, we need a measure that can clearly identify important vertices on the network.

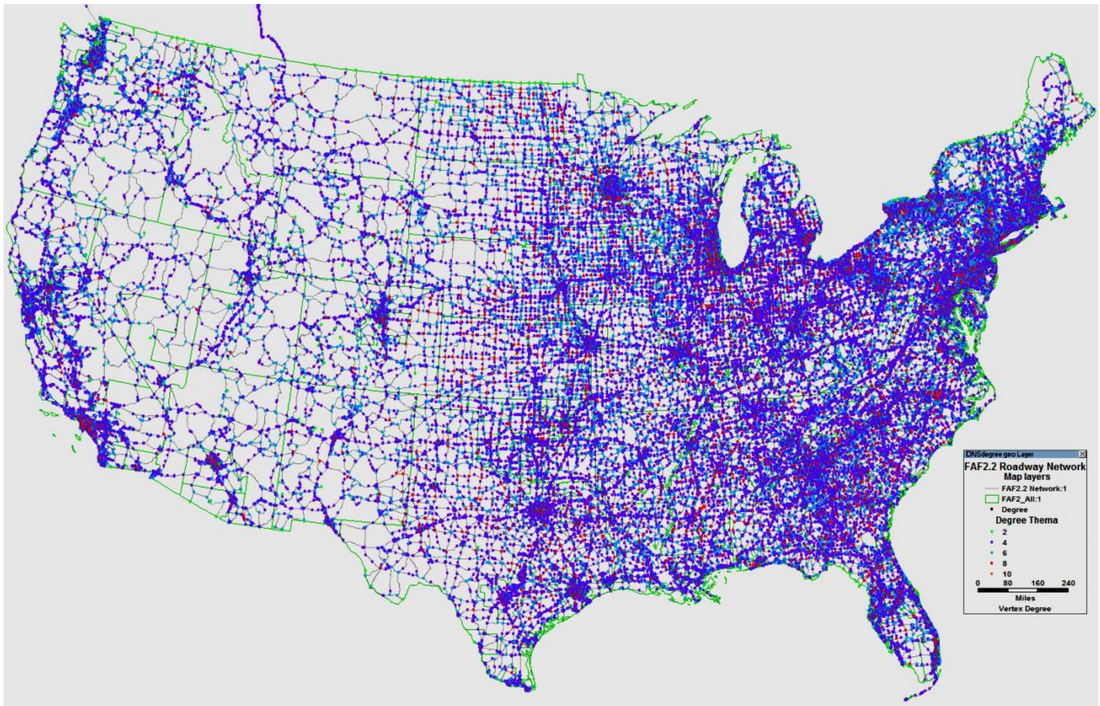

Figure 6.4: Degree - roadway network.

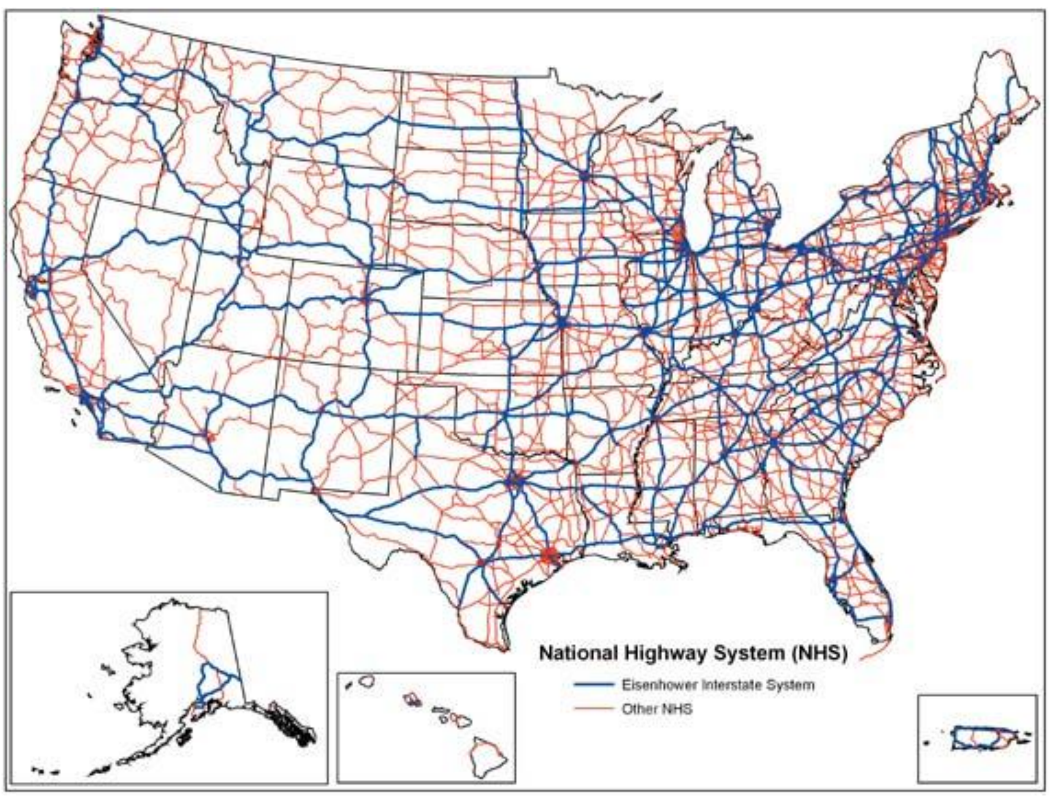

Figure 6.5: National highway system.

Closeness centrality

The closeness centrality measure shows that the central U.S. is very well connected, directly linked to all other vertices in the Midwest (the center) (Figure 6.6). The measure decreases in both directions away from the center; the regions reach out about 600, 1500, 2500, 3000 miles to the west. The lower the closeness centrality, the easier to disconnect vertices, because they are less connected.

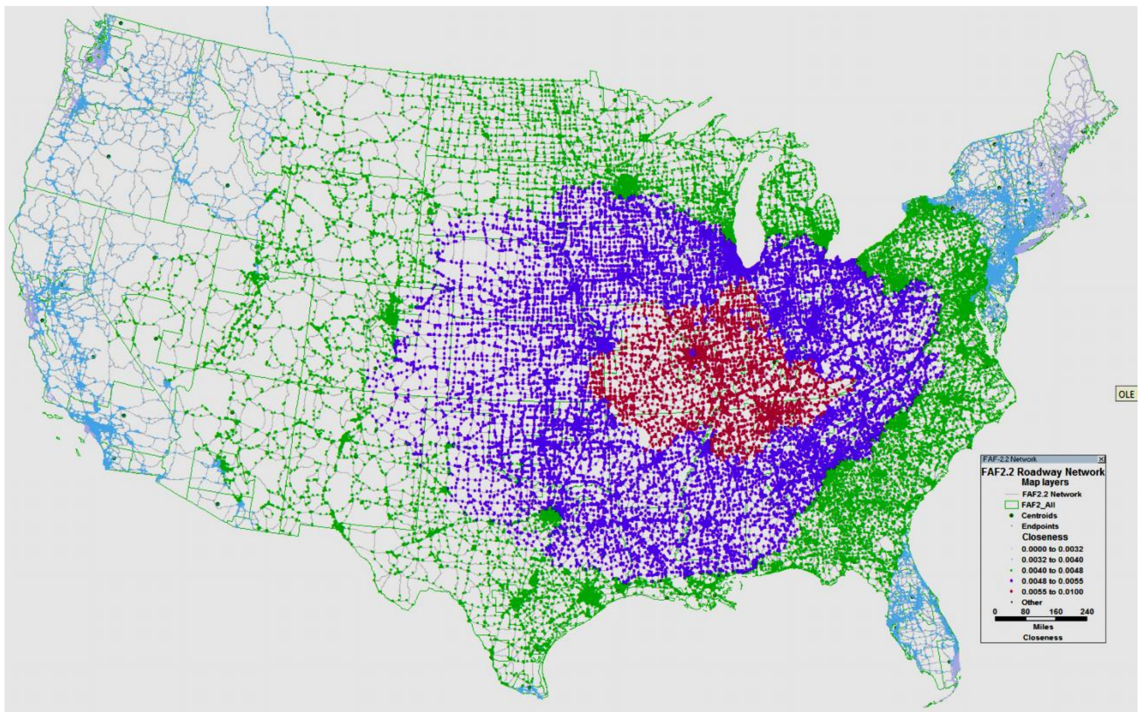

Figure 6.6: Closeness centrality of roadway network.

Cut vertices

A network is called bi-connected if for every triple of vertices $a, v,$ and w, there exists a chain between w and v, which doesn't include a [Nooy et al, 2005]. Simply put, a network is called bi-connected if, after removing any vertex, the network remains connected [Nooy et al., 2005]. In order to find cut vertices and bridges we look for the components with at least 2 vertices.

The bi-component vertices list (Table 6.2) indicates a sequential number of the bridge or bi-component to which a vertex belongs. From this list, we can identify the number of cut vertices as well as the how many components the network can be divided with the cut vertices.

Table 6.3 Bi-component Vertices in FAF$^{2.2}$ Roadway Network

```
1. Vertices belonging to exactly one bi-component of FAF2.2 Roadway
network (135589)
-----------------------------------------------------------------------
-
Dimension: 135589
The lowest value:  1
The highest value: 4489
Number of values larger than 999999997 (missing values): 4239

Frequency distribution of cluster values:
```

Cluster	Freq	Freq%	Valid%	CumFreq	CumFreq%	CumValid%	Reprsnt.
1	1	0.0007	0.0008	1	0.0007	0.0008	104966
2	1	0.0007	0.0008	2	0.0015	0.0015	139551
3	1	0.0007	0.0008	3	0.0022	0.0023	15684
6	1	0.0007	0.0008	4	0.0030	0.0030	14921
7	1	0.0007	0.0008	5	0.0037	0.0038	134501
………	…	…	…	…	…	….	….
………	…	…	…	…	…	….	….
4486	2	0.0015	0.0015	131345	96.8700	99.9962	136555
4487	1	0.0007	0.0008	131346	96.8707	99.9970	136584
4488	2	0.0015	0.0015	131348	96.8722	99.9985	136557
4489	2	0.0015	0.0015	131350	96.8736	100.0000	136924
Sum	131350	96.8736	100.0000				
Unknown	**4239**	3.1264					
Total	135589	100.0000					

Articulation points (cut vertices) list (Table 6.3) indicates the number of bridges or bi-components to which a vertex belongs: 0 for isolates, 1 for a vertex that belongs to exactly two bridges or bi-components, and so on.

In search of the cut vertices, we found out that there are 4239 cut vertices in the FAF$^{2.2}$ roadway network, given with the 999999997 code, as a result of which the network may divide into 4489 bi-connected components (given in the bi-component program output). There are no vertices that are isolated, and there are 131350, 4075, 162, and 2 vertices that belong to 1, 2, 3, and 4 bridge(s) or bi-component(s) (given in the articulation point program output).

Table 6.4 Articulation Points in FAF2.2 Roadway Network

```
Articulation Points in FAF2.2 Roadway Network (135589)
-----------------------------------------------------------------
Dimension: 135589
The lowest value:  1
The highest value: 4

Frequency distribution of cluster values:

   Cluster      Freq     Freq%   CumFreq  CumFreq% Representative
 ---------------------------------------------------------------
         1    131350   96.8736    131350   96.8736 1988
         2      4075    3.0054    135425   99.8790 2002
         3       162    0.1195    135587   99.9985 2161
         4         2    0.0015    135589  100.0000 114975
 ---------------------------------------------------------------
       Sum    135589  100.0000
```

Cut vertices of the roadway network are shown in Figure 6.7, with pink color. Most of the cut vertices are on the borders of the roadway network, and others are spread through the network.

By definition, a cut vertex plays a critical role in disrupting the flows. For instance, the MSAs, we use to define origin and destination locations (instead of every household or business) on $FAF^{2.2}$ network, combine all demand and supply of the location it represents. Because it is a single vertex connected to the network via a bridge, the removal of this bridge or the end vertex of this bridge results in complete loss of the respective supply and demand of this MSA. Hence, protection of this bridge or cut vertex is of utmost importance; and by looking at cut vertices, we can identify this vulnerability. On the other hand, some cut vertices separate only one vertex from the main graph which may have no associated flow. Therefore, additional measures to aid in identification of critical vertices are needed.

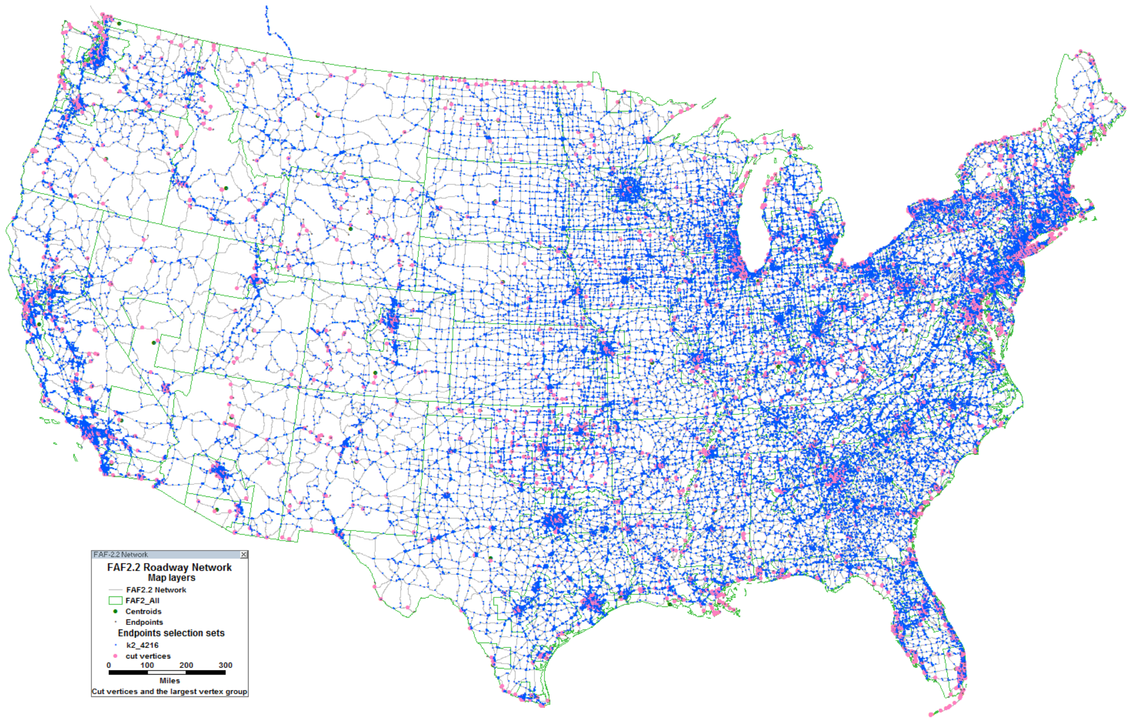

Figure 6.7: Cut vertices on the roadway network.

Betweenness

The betweenness value shows how crucial a junction of a transportation network (a vertex in a network) is to the transportation of flow (freight) through the network. A high betweenness value suggests that the vertex is an important intermediary; in the case that it is removed a number of flows are disrupted or must take longer detours to reach their destination. In Figure 6.8, the red colored vertices show the nodes with the largest betweenness values, which match some major highways, particularly in the east-west direction (compare to Figure 6.5).

Since highways carry most of the freight flows and since betweenness can identify major highways, this measure can be used to identify critical locations for freight transportation. Betweenness measure results of the Oklahoma roadway network is given in Figure 6.9, but it does not produce a significant pattern.

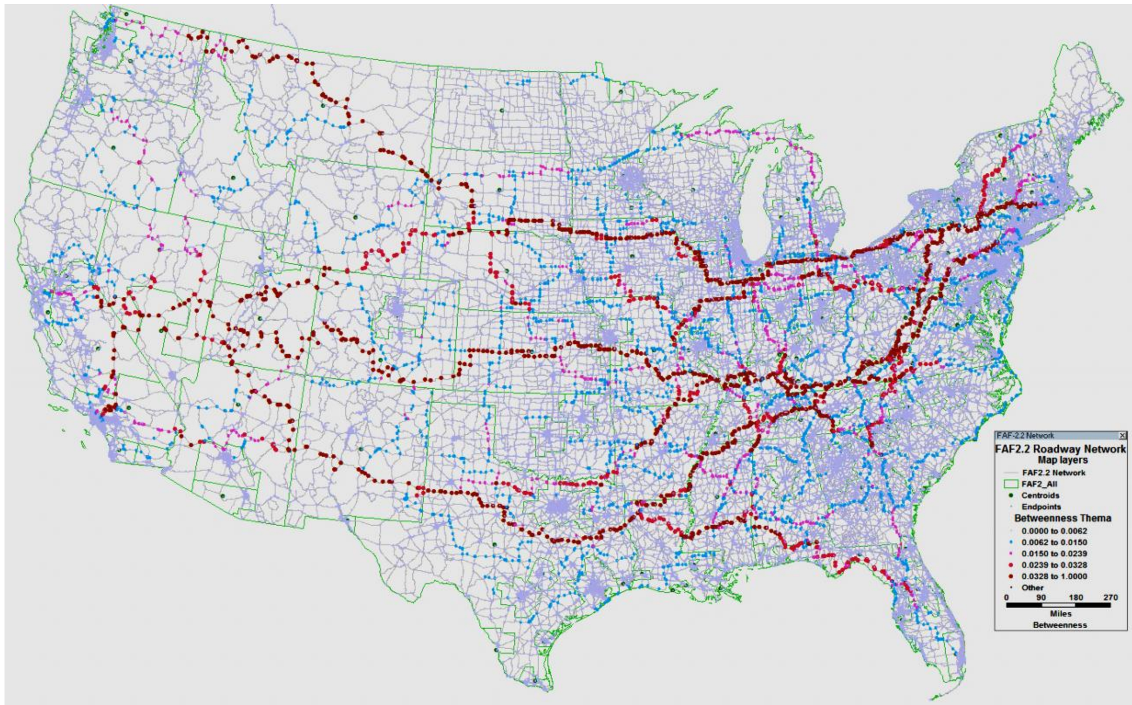

Figure 6.8: Betweenness - roadway network.

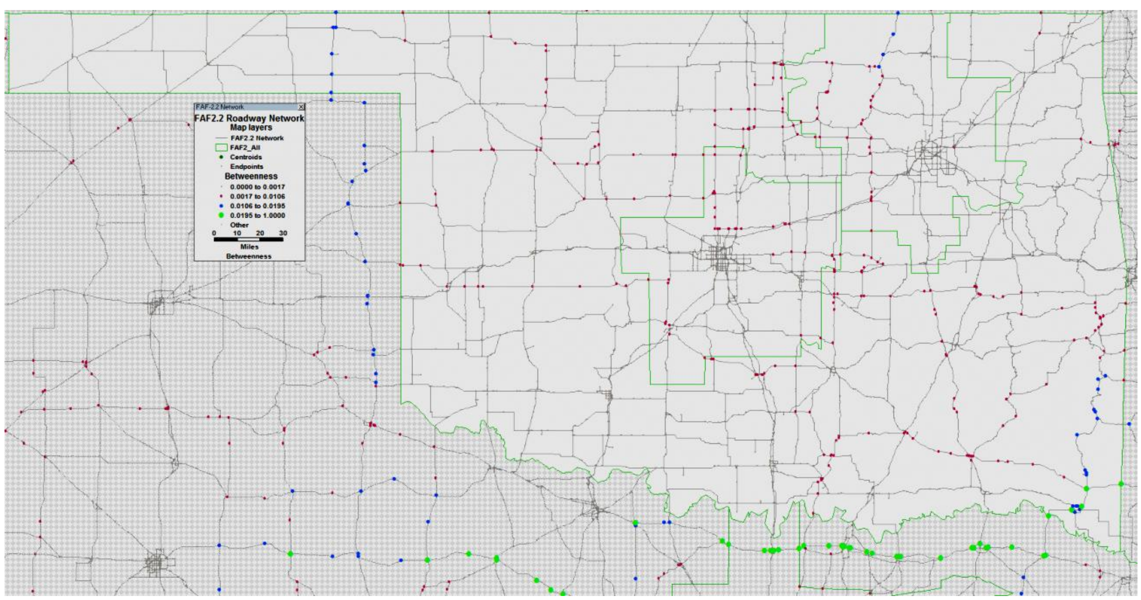

Figure 6.9: Betweenness - roadway network, OK.

Identifying critical freight locations

Our objective is to identify the vulnerable locations, vertices or group of vertices. After the initial network analysis we use the cut vertex and betweenness attributes because of their contribution in identifying the critical network components, as well as the transportation flow attributes.

The procedure assumes that the vertices correspond to junctions or origin/destination points that represent MSAs, and vulnerable vertices have one or more of the following properties:

- Be a cut vertex
- Have a high betweenness score
- Have a high freight flow

All cut vertices are critical locations because removal of a cut vertex results in disconnected components. However, being a cut vertex is not sufficient to define a critical location. For instance, a subgraph G' may be connected with two vertices, n_1 and n_2 to a second subgraph G'', where $G = G' \cup G''$. Even though both n_1 and n_2 are critical locations, because removal of either vertex will disrupt the flow, neither is a cut vertex in G since removal of either vertex does not disconnect the graph.

Removing a vertex with high betweenness from the graph (or removing an edge with a high edge-betweenness) breaks many shortest path routes between vertices in the original graph; this results in flow disruptions or detours. Therefore, a high betweenness in a network can be a criterion to identify critical locations.

Lastly, freight flow shows how much flow is transferred through the corresponding junction. We use high freight flow as a criterion in defining vulnerability, because if the junction is serving a high freight flow, then it is critical and its failure disrupts the freight flow.

The freight flows are calculated using the TransCAD software, using the AON assignment model, given in Figure 6.10. The map shows the freight flow movement on the roadway network based on the shortest path assignment model.

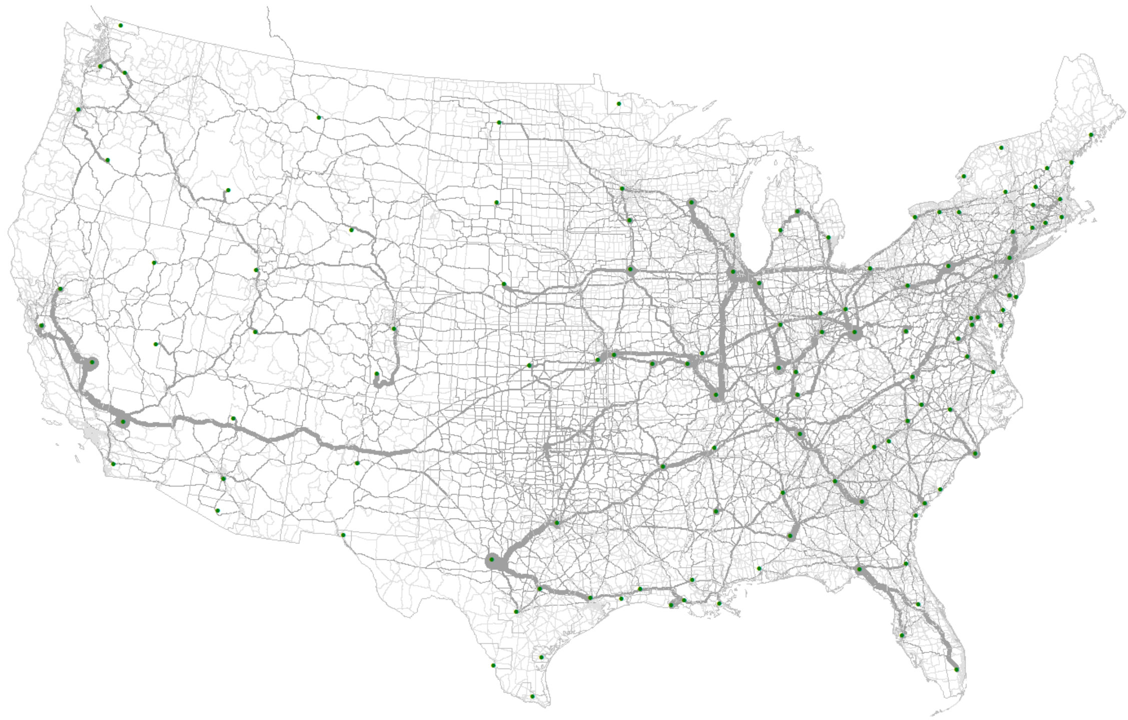

Figure 6.10: AON flow on roadway network.

Next, we determined the cut vertex and betweenness attributes of the roadway network using the Pajek network analysis software. The spatial distribution of cut vertices can be seen in Figure 6.11. Some of the cut vertices are located at the borders, the rest are spread on the network in groups and sometimes individually. If we remove any of these vertices, there will be at least one vertex that will be disconnected from the main network.

In Figure 6.12, the vertices are re-sized according to their betweenness values; higher betweenness is presented with a larger node size.

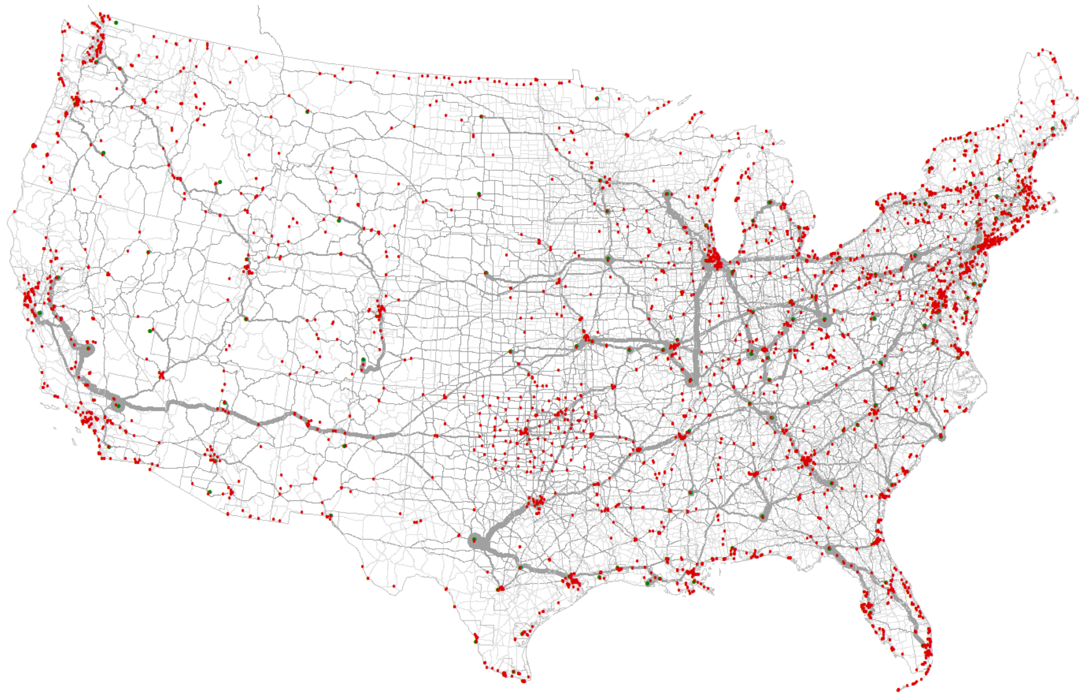

Figure 6.11: AON flow and cut vertices on roadway network.

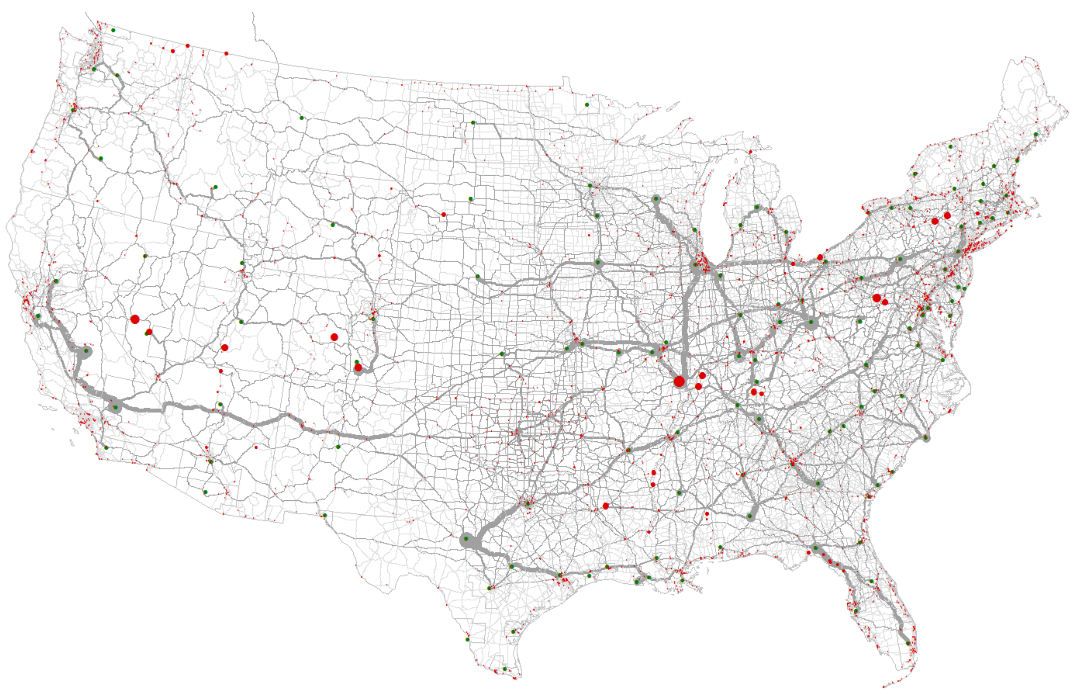

Figure 6.12: Cut vertices scaled with betweenness measure, AON.

The Figure 6.13 highlights three locations: Chicago IL, IL remainder, and Colorado, which show high values of the attributes suggesting possible vulnerable locations.

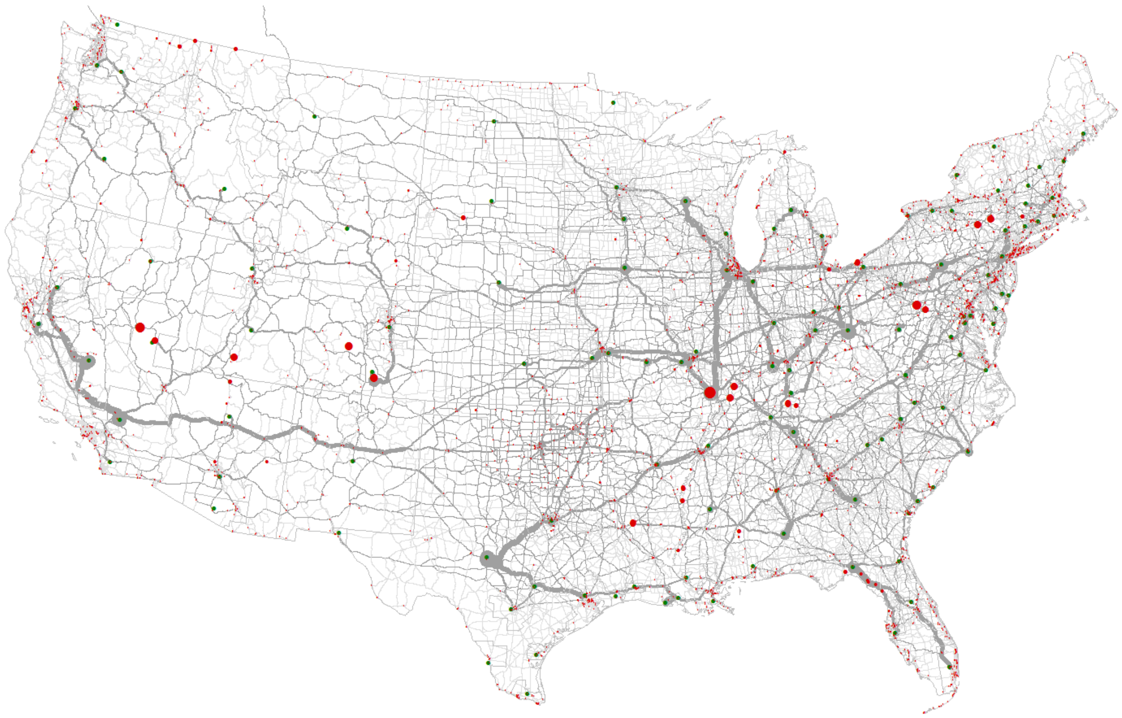

Figure 6.13: Possible vulnerable locations based on flow, cut vertex, and betweenness attributes.

Two MAVT methods, SAW and AHP, are used to synthesize these attributes to find vulnerable locations on the roadway network. The next sections present the results of these methods.

SAW Method

According to the SAW method, the decision maker estimates weights of attributes. The following weights are chosen for betweenness, cut vertex, and freight flow attributes: .35, .2, .45, respectively. The vulnerable locations are shown in red in Figure 6.14. Chicago, IL and IL remainder are at the top of the list matching the visual selection on. Other vulnerable locations are also shown on the map that matches the criteria.

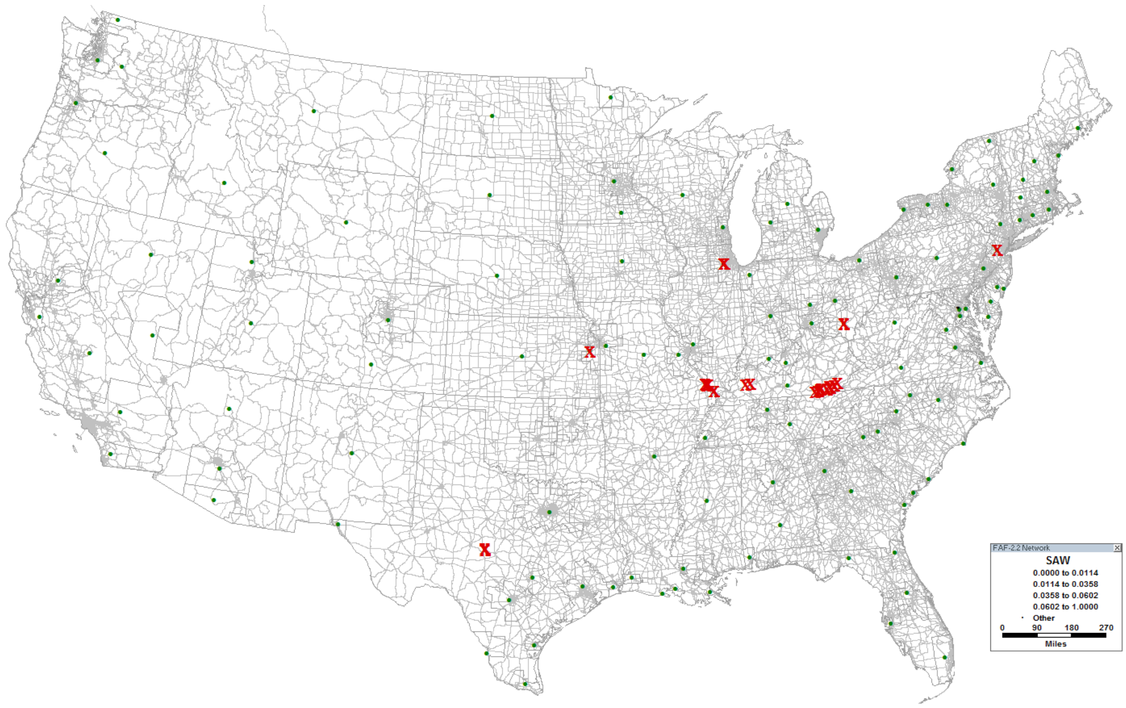

Figure 6.14: SAW method - top vulnerable locations.

AHP Method

In AHP, decision maker judges the attributes in pairs (for instance, using the SuperDecision tool, Figure 6.15), and weights of attributes are calculated based on the pairwise comparison. The inconsistency index (ICI) is 0.05 which is less than .1, suggesting a consistent weight assessment (which can also be calculated with the SuperDecision tool, Figure 6.16).

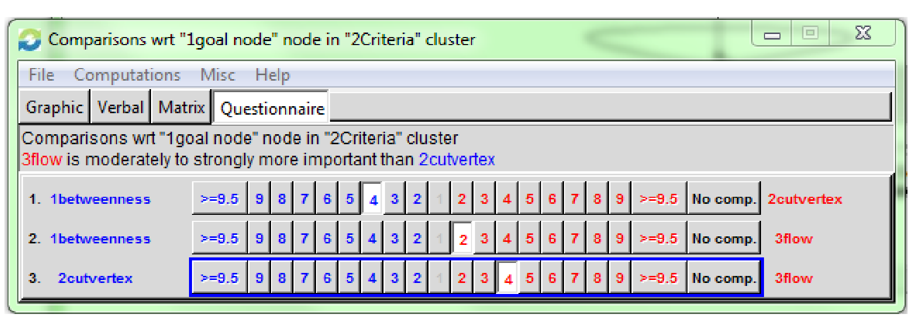

Figure 6.15: Pairwise attribute comparison.

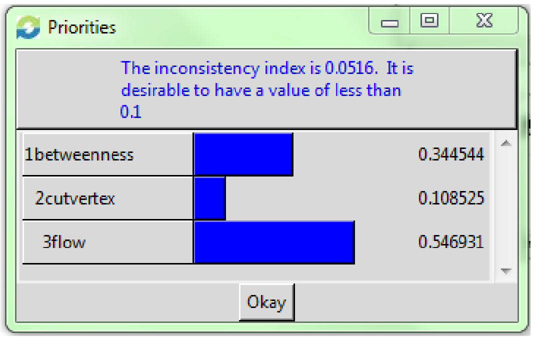

Figure 6.16: Attribute weights.

According to AHP (Figure 6.17), Chicago, IL, and the remainder of IL are selected, which matches the previous two selections. In addition to other vulnerable locations that SAW selected, AHP results in selections that are spatially apart from one another.

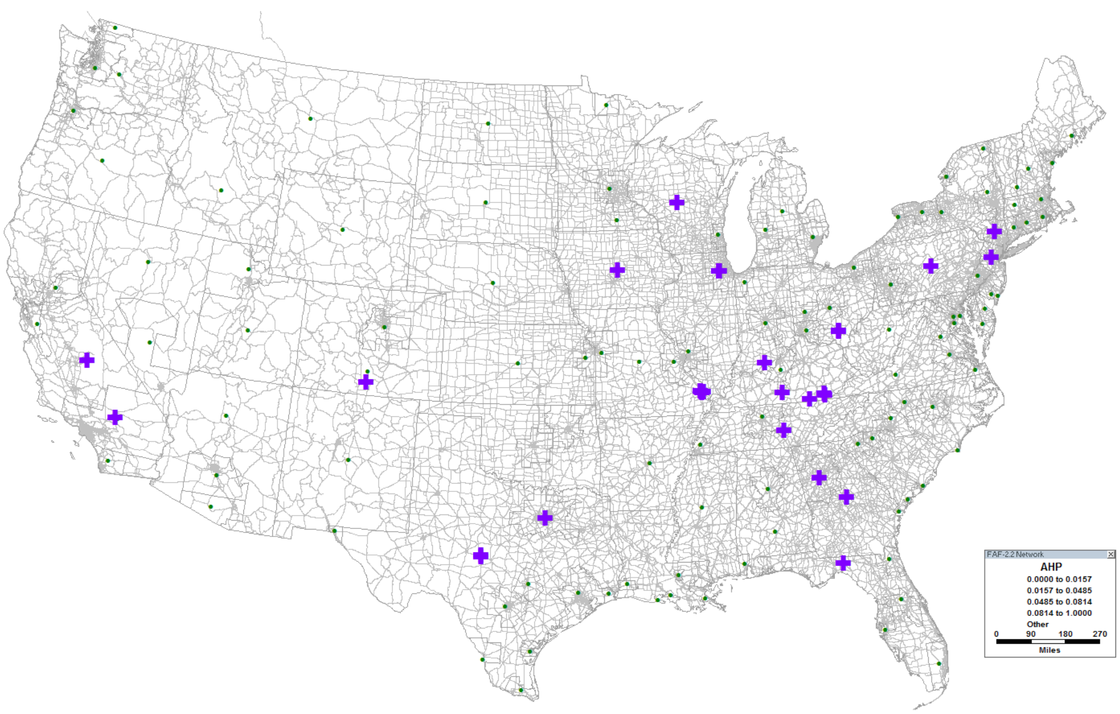

Figure 6.17: AHP top vulnerable locations

We see that using a synthesis of graph theoretical and freight flow attribute in MAVT provides valuable information on vulnerable freight locations. In both SAW and AHP methods, critical levels of the attributes are identified. This information can be used in long term strategic planning of freight transportation.

6.5 Case Study: Vulnerability of Freight due to Hurricane Katrina

In this section we research the vulnerability of the freight transportation network due to Hurricane Katrina, which devastated the LA-AL-MS region and caused major disruption on the roadway network. The freight disruption due to the disaster is investigated previously in chapter 5. Here we model the pre-disaster and post-disaster vulnerability and discuss how the disaster changed the vulnerability on the U.S. roadway network.

Let's look at the betweenness measure at pre- and post-disaster cases in 6.18 and Figure 6.19 comparison of the two maps show that the betweenness values at the southern part of the U.S. change after Hurricane Katrina. The highest betweenness change is particularly observed on I-55 towards north, I-10 to the west, and also I-12 and I-59 at the north-east, whereas the New Orleans area has lower betweenness values. Recalling the post-Katrina freight flow, given in Figure 5.6 (top), the freight flow to the disaster area diminished due to the flood, and the U.S. freight flow shifted towards the north. There was also a slight increase in the number of cut vertices due to the damaged bridges and highway sections at the disaster regions.

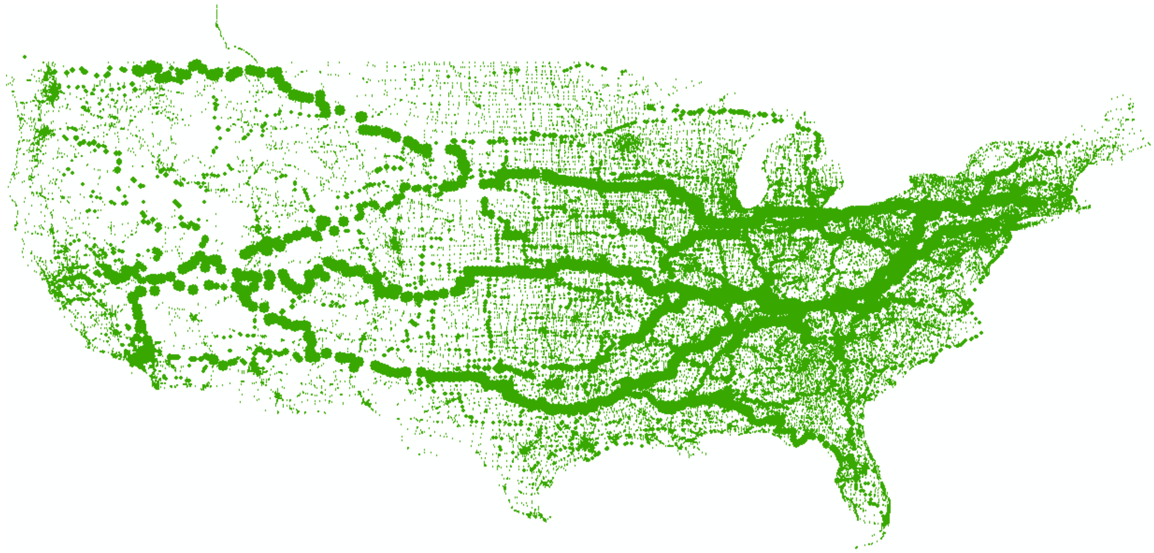

Figure 6.18: Betweenness, pre-Katrina

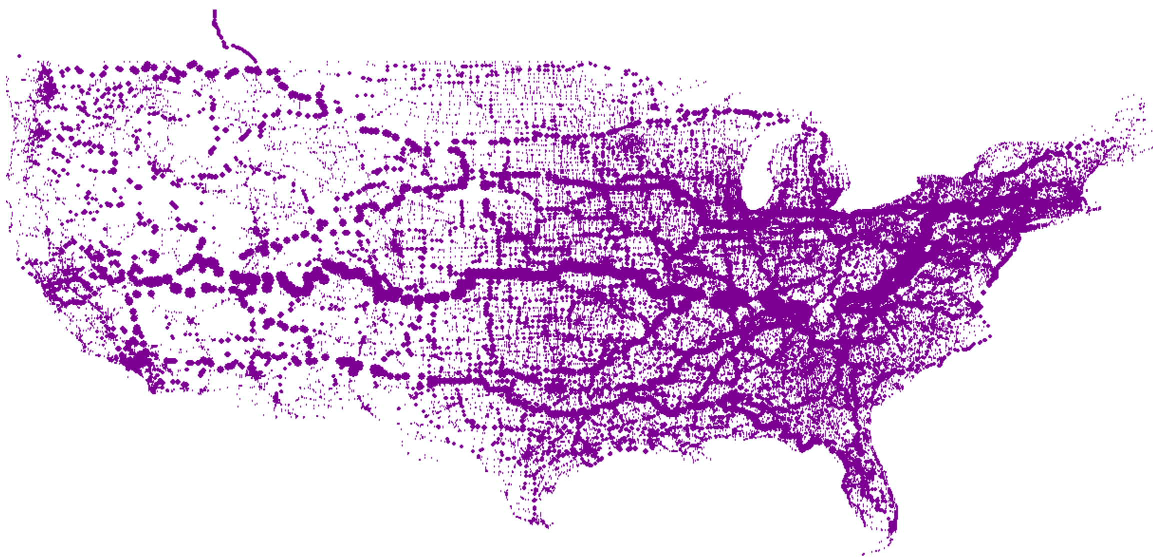

Figure 6.19: Betweenness, post-Katrina

The betweenness Figures 6.18 and 6.19 show that after the disaster southern freight flows were disaggregated to smaller flows towards the east. Given the New Orleans area was flooded, the 3 state area had several unavailable roads and bridges. As presented on the figure, the majority of the increased betweenness is at the disaster region, but it also stretches away.

We use the AHP model and normalize the parameters to eliminate the different scales and units. Using the AHP procedure, for which we previously defined the respective weights for the betweenness, the cut vertex and change in freight flow, we find the top 5 locations with the highest vulnerability score, shown in Figure 6.20, and the top 20% of the AHP scores are shown in Figure 6.21. The highest vulnerability increases are at the busiest locations in mid-west, similar to the pre-disaster conditions. As we consider more of the increased vulnerability scores, the I-70 east-west corridor continues to light up. This increased vulnerability suggests that after the Hurricane Katrina, I-57 and I-70 corridors became even more vulnerable than the pre-disaster conditions.

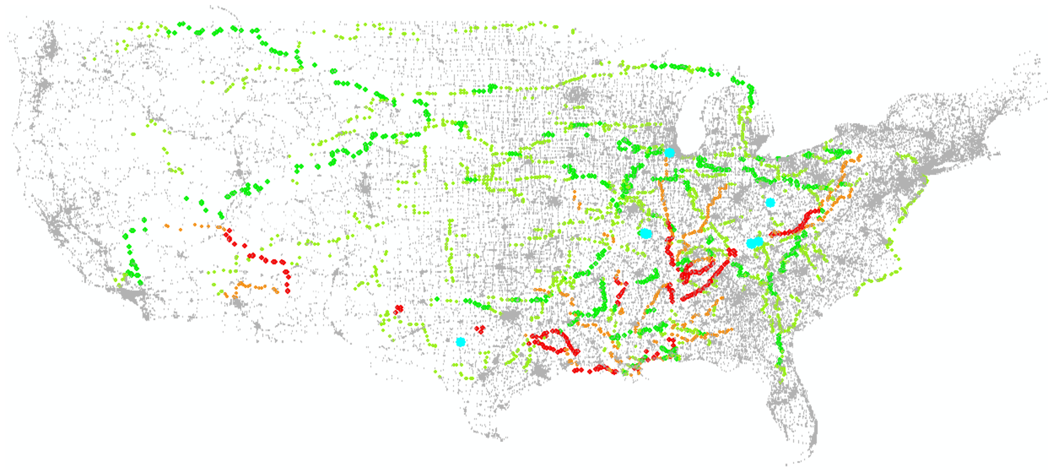

Figure 6.20: Increased vulnerability due to Hurricane Katrina, AHP (light blue locations)

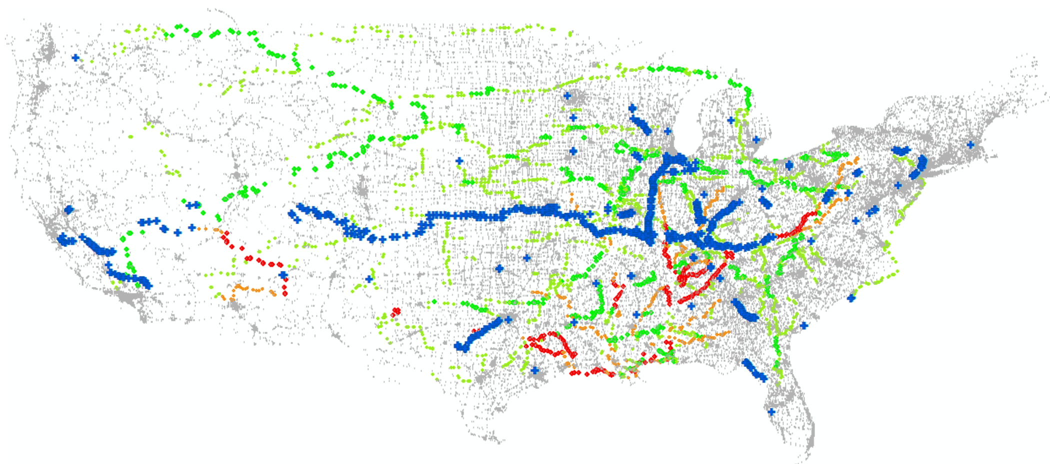

Figure 6.21: Top 20% increased vulnerability due to Hurricane Katrina, AHP shown with blue cross.

6.6 Conclusions and Future Research Directions

Continuous threats on critical infrastructures, one of which is transportation systems, increased the attention on vulnerability, risk, and reliability research. While the literature is vast on application of such terms, the definitions vary according to disciple, as well as the relationship between these terms. In this chapter, we discuss vulnerability, risk, and reliability in the context of transportation systems, specifically freight transportation. Unlike other definitions of vulnerability, we define vulnerability as a multi-faceted dynamic attribute, via the freight transportation system's characteristics, such as the network and flow characteristics. As we control the change in these facets and by reducing threats, we can be more efficient and effective in minimizing the vulnerability of freight transportation.

We first analyze which network attributes are helpful in identifying critical locations. We show that the U.S. roadway network is the most connected in the Midwest (clustering coefficients) and that U.S. highways have high betweenness values, showing the important role that they carry. Next, we define the vulnerable vertices to have three characteristics: be a cut vertex, have a high betweenness score, and have a high freight flow. We also discuss MAVT methodology, which we use to synthesize different characteristics of the freight transportation system. With this synthesis we account not only for the network properties but also the freight behavior. The two methods we applied, SAW and AHP, both selected vertices that are in metropolitan locations to have the highest vulnerability. Major difference between the selections of these methodologies is that AHP selects nodes that are spatially more separated vertices. Further analysis on how weights should be determined and different MAVT methodologies, as well as MAUT, can be explored to guide in disaster preparedness.

In case of the Hurricane Katrina of 2005, in the post-disaster freight transportation network analysis, we observed that the vulnerability increased at I-10, I-12, I-59, and I-55 which surround the disaster region as well as the I-70 and I-57 corridors that are further away to the north.

Disasters are times of chaos, critical communication and collaboration, and also when the scarcest resources have to be strategically located. By managing the disaster with better tools, we can better make decisions on where to look for possible vulnerabilities, and hence, provide aid, even prevent any secondary disasters. We aim to initiate further research in this space, as well as with this modeling approach, to benefit transportation planners and policy makers, and provide guidance for the preparedness and mitigation efforts, as well as in long term planning.

Chapter 7: Conclusions and Future Research Directions

This dissertation presents the published works on freight transportation, in which we discussed and researched questions, such as how freight flow behavior at different geographic analysis levels, its relationship with the economy, the impact of extreme events on freight flow, and freight flow vulnerability. A formal framework for analyzing impact of extreme events on freight flow is developed with illustrations on roadway networks. Relating this impact to the freight network vulnerability, we focus on the road network and freight movement characteristics to formulate and illustrate the vulnerability of roadway network.

In this chapter first we summarize the previous chapters and direct attention to future research questions.

7.1. Explaining the Link Between Freight Movement and Economy

Freight flow movement provides a unique perspective in understanding national and local economic changes. In Paper I, we develop a set of measures, namely from, to, within, and through freight flow which we use to classify a state or MSA as production, attraction, and through states or MSAs. Production and attraction freight flow percentages are good indicators of the state's dependency on other states for its commodities. In general, we can say that a production state is more self-sufficient than an attraction state. Based on the $FAF^{2.2}$ data, we find that some producing states become less productive, whereas some states become significantly more productive while the U.S. total increases during the same interval, showing the dynamic nature of state economies. The within freight flow typically increases over time as the population increases. Through flow of a state, on the other hand, shows the use of transportation network to satisfy the high production and attraction of other states. Hence, states with higher through freight flow may need to consider more federal funding to upgrade their roadway networks or charge traffic tolls for through flow, though this is a politically sensitive topic worthy of further research.

The forecasts of the disaggregated freight flow can be used in transportation planning and cost association, i.e. by focusing on the specific freight routes for within freight flow for the state or can be developed into a tracking mechanism to observe and predict the changes at the to-freight and from-freight partners.

The link between national/local economies is shown with the regression model, where we explain freight flows by employment, establishment, revenue, and payment. We show the strong relationship between these economic indicators and the state level production, attraction and within freight flows. However, the regression result explaining the through flow with the same economic indicators is not statistically significant, which can be another future research question. In addition, considering the network capacity and other freight modes can improve the results. Further research on the socioeconomic relationship between freight and freight movement can lead to better decisions and policies for freight transportation.

7.2 Freight Movement and Extreme Events

Extreme events impact many aspects of our lives, such as failed lifelines and disrupted transportation networks, similarly the freight transportation. Using the I-40 bridge collapse case, we determined the effects of this disruption on the roadway network on the redistribution of freight flow at local, regional, and national levels. Results show that the disaster impact is high in local areas and freight flow at any part of the network may be affected significantly, depending on the severity of the extreme event. This indicates the distance from the disaster location isn't a key variable in measuring flow changes and impacts. Therefore, gravity models, which use the distance as a multiplying factor and assume the impact decreases with the distance to disaster location, may not be valid in cases of regional or national analysis of the impact. We provided two approaches for analyzing the impact of an extreme event, in this case a bridge collapse, which can be used by transportation planners to consider immediate effects of an extreme event (Paper II). In this research we used 114 FAF regions and 77 counties of Oklahoma to analyze the freight flow changes in Oklahoma specifically. However, to make this research more accurate, a finer spatial unit, i.e. counties, can be used instead of the 114 FAF regions. Counties can be divided into businesses, which unfortunately is not available due to confidentiality issues.

Extreme events, such as hurricanes and earthquakes, may result in more complications than a single bridge collapse, such as multiple disruptions on the network and varying recovery phases. We developed a general framework utilizing traffic independent (distance) and traffic dependent (VMT, VHT) measures to analyze and compare freight flow changes and re-routing under different recovery strategies and scenarios. We show that, given the scenario specifications, publicly available freight databases and transportation networks can be used for analysis. (Paper III). Further research in freight flow changes with respect to FCLASS and RUCODE characteristics of the network can provide insight into how we can manage the rerouted traffic after extreme events. At a time where the number of disasters as well as the cost associated with extreme events are increasing, therefore the research on the extreme event impact analysis now is vital to minimize losses.

In general, more reliable performance measures, as well as comprehensive, more representative and multi-level databases are fundamentally needed to improve our understanding of the extreme conditions on transportation systems.

7.3 Vulnerability of Freight Flows on Roadway Networks

Increasing number of extreme events, more specifically man-made disasters and targeted extreme events, to impair the national security directed the research community to investigate the vulnerability of critical infrastructures, one of which is transportation networks. We focused on the definition of freight flow vulnerability and how to quantify it. We discuss several characteristics of freight transportation and develop an approach using graph theory and multi-attribute value theory to assess the vulnerability of freight.

Taking a systems perspective of the freight transportation systems, we sliced the characteristics which inherently carry vulnerability to the larger system. We defined service layer and network layer factors to define the multidimensional dynamic variable, which is the vulnerability of freight transportation system. Further research into how weights can be calculated, the sensitivity to expert's input as well as other methodologies which incorporate probabilistic threat assessment will greatly improve preparedness for disasters and benefit in minimizing and eliminating unfortunate loses.

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